WHY DO OPTION INTRODUCTIONS DEPRESS STOCK PRICES? HETEROGENEOUS BELIEFS, MARKET-MAKER HEDGING, AND SHORT SALES

By

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by

Bartley R. Danielsen

To my parents, Albert and Eleanor.
They encouraged creativity and curiosity.

To my guiding star, Patricia.
She shines bright in the cold and black of night.
I thank God for sharing the radiance with me.

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WHY DO OPTION INTRODUCTIONS DEPRESS STOCK PRICES?
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Early studies found that option introductions tend to raise the price of the underlying stock. More recent research indicates that post-1980 option introductions cause negative returns in the underlying stock. Previously, increased short-sale activities following option listing have been noted. This dissertation presents both theoretical and empirical evidence that the observed increases in short selling are related to the recently recognized negative abnormal returns. I develop a model that identifies stock trading and market characteristics that can be used to predict the magnitude of individual stock price declines. Then, I test the validity of the model. I conclude that ex-ante trading characteristics are valuable in predicting the magnitude of the price decline of the underlying security upon option introduction.

The contributions of this dissertation are four-fold. First, I empirically document a specific mechanism through which option trading affects stock prices. Second, this

dissertation represents the first empirical test of competing theories on the impact of short-sale constraints on stock prices. Third, the dissertation documents a previously unknown anomalous relationship between ex-ante observable security-specific trading characteristics and subsequent abnormal returns. Finally, my analysis uses the previously unutilized laboratory of option listings for examining the elasticity of demand curves for common stocks. My results add to the accumulating body of evidence on the presence of downward sloping demand curves for individual equity securities.

CHAPTER 1
INTRODUCTION

Several papers have empirically examined the returns of underlying stocks around the introduction of equity call and/or put options. Early studies by Branch and Finnerty (1981), Detemple and Jorion (1990), and Conrad (1989) find positive excess returns in narrow windows around call option introductions. Sorescu (1997) also finds positive abnormal stock returns for options introduced prior to 1981. However, following adoption of new option market regulations imposed by the Federal Reserve in 1980, Sorescu observes option introductions have been accompanied by a negative stock price response.

A possible explanation for why option introductions coincide with a stock price decline is that options provide a mechanism for pessimistic investors to establish a short position in the stock when costs of direct short-sales are prohibitively high. Asquith and Meulbroek (1995) produce a well-articulated list describing the reasons why "normal" traders find establishing a short position to be more costly than establishing a long position. In contrast, option market makers enjoy much lower short-selling costs. In particular, while most investors earn no interest on short-sale proceeds held by their broker, option market makers, as large and specialized traders, can negotiate better terms with brokers who lend them shares for short selling. These market makers earn interest, known as the "short stock rebate," on the proceeds of the broker-held short-sales. The interest payments they receive are not token sums, but are quite close to the rate they pay

for margin loans to fund long stock positions. For example, in August 1997, one market maker paid 6% for margin loans and received a short-stock rebate of 5.375%. In contrast, inquiries with two large retail brokers revealed proceeds from a $1,000,000 short-sale of Coca-Cola stock would earn no interest while the short position remained open, but a $1,000,000 margin loan to buy Coca-Cola through either brokerage would accrue interest at rates almost two points above the market maker's quoted rate.

As an alternative to high-cost short sales, when options are available on a stock, pessimists may buy puts and/or write calls to produce payoffs that mimic an actual short sale. Option market makers, acting as counter-parties to investor initiated transactions, hedge their positions with other option market transactions or via low-cost short sales. Thus, as investors establish short positions via options and market makers hedge their exposure though the normal market making mechanism, increased short sales drive down the equilibrium price of the stock.

This paper provides evidence that the observed price decline in the underlying stock is related to changes in reported short interest. Using the set of all equity option introductions between 1980 and 1995, I show a cross-sectional correlation between the level of increased short selling and the magnitude of the option related abnormal stock returns. Moreover, the dissertation demonstrates that the additional short selling and abnormal return can be predicted based upon characteristics of the stock in advance of the introduction event.

The contributions of this dissertation are fourfold. First, I empirically document a specific mechanism through which option trading affects stock prices. Second, this dissertation represents the first empirical test of competing theories on the impact of

short-sale constraints on stock prices. Third, the dissertation documents a previously unknown anomalous relationship between ex-ante observable security-specific trading characteristics and subsequent abnormal returns. Finally, my analysis uses (for the first time) the laboratory of option listings to examine the elasticity of demand curves for common stocks. My results add to the accumulating body of evidence on the presence of downward sloping demand curves for individual equity securities.

This dissertation follows the following format. Chapter 2 provides the Literature Review that draws together three distinct branches of financial economics. I first review the theoretical and empirical literature on option introduction price effects. Second, I examine the competing literature regarding price effects of short-sale constraints, and finally, I address the small, but growing, body of work demonstrating downward sloping demand curves for individual securities.

Chapter 3 considers various institutional details that the reader will find useful in understanding both the model presented in Chapter 4 and the empirical tests conducted in Chapter 5. Institutional details regarding both short selling and option market making are discussed in Chapter 3.

Chapter 4 presents a model in the spirit of Jarrow (1980) that shows how option introductions might depress stock prices. The model also produces a set of firm-specific characteristics that should be correlated with the magnitude of price decline.

Chapter 5 provides a set of cross-sectional tests of the model and, more generally, examines the relationship between option-introduction stock returns and various firm-specific characteristics including short interest changes. The tests utilize an exhaustive set of data on options introduced prior to 1996.

Chapter 6 presents extensions on the tests conducted in Chapter 5. These tests for the existence of cross-sectional differences in the degree of option-listing-related short sale constraint relaxation. Although the theoretical model presented in Chapter 4 does not contemplate differing degrees of short sale constraint relaxation, we can presume that some firms are more short sale constrained than others, ex-ante. This difference can be expected to impact both the change in share price and the change in short interest.

Chapter 7 is a brief conclusion summarizing results from the model and empirical tests conducted in the previous chapters.

CHAPTER 2
REVIEW OF LITERATURE

Introduction

This dissertation examines the relationship between short sales and option introduction induced stock returns. In doing so, three distinct branches of the finance literature become entwined: the option introduction literature, the short-sale constraint literature, and the literature examining "price pressure" or demand curve slopes. In this section, I review the literature of each branch in turn and discuss its relationship to this paper.

Option Introduction Literature

The effects of option introductions on underlying stock prices have been investigated theoretically by numerous authors. Although Black and Scholes' (1973) seminal option pricing work assumed derivatives to be redundant securities, early theoretical papers examined how option introductions might expand the opportunity set enjoyed by investors. (See Ross 1977, Hakansson 1978, Breeden and Litzenberger 1978, and Arditti and John 1980.) A practical variant of this observation is that options provide investment possibilities that transaction costs or regulation otherwise discourage or prohibit in an option-free world.

Of particular importance in the motivation of this paper are two potential option-bridging cost/regulatory constraints--short-sale constraints and portfolio rebalancing costs. Short sellers face a host of such constraints including 50% margin requirements, search

costs for borrowing shares, the SEC Rule 10a-1 uptick rule for exchange traded securities, and foregone interest on sale proceeds. The full gamut of short-sale restrictions are discussed in Chapter 3.

Rebalancing costs might best be highlighted by considering the very bullish investment strategy achieved by the purchase of out of the money call options. In theory, such a position can be established by borrowing cash and investing the proceeds in stock. Options are considered redundant securities in the sense they generate payoffs that theoretically can be produced via debt and stock combinations. The Black-Scholes model is derived from this theoretical redundancy in that an option can be priced from a potential arbitrage between options and a stock/bond mix. In practice, however, perfect duplication of the bullish call buyer's payoff structure using a debt/stock combination faces the prohibitive cost of rebalancing the mix continuously. Option trading allows a single transaction, the call purchase, to create and maintain the desired payoff structure.[1] Short-sale constraints and stock portfolio rebalancing costs are a small subset of many cost/regulatory impediments that might be bridged by option trading.

The early papers by Ross (1977), Hakansson (1978), Breeden and Litzenberger (1978) and Arditti and John (1980) acknowledge new equilibrium stock prices might be derived from the introduction of a derivative, but they offer no guidance on whether these prices are higher or lower than the prices of non-optionable stocks.

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[1] To a lesser extent, many frictions encountered in trading levered stock positions may be faced in the derivatives market as well. See Figlewski (1989). Nevertheless, under many circumstances, options markets enjoy fewer frictions than the stock and debt markets. For example, this dissertation presumes investors wishing to hold a levered short stock position may find an option to be a better tool than direct short stock holdings because short-sale costs are high for small investors.

Subsequent papers have examined whether optionable stocks have higher or lower equilibrium prices. Unfortunately, this literature leaves the question unresolved as various assumptions in the models provide differing results. Given certain initial endowments and state probabilities, Detemple and Jorion (1990) show option introduction may produce higher equilibrium prices. They also note the possibility of lower stock prices with differing initial endowments. Detemple and Selden (1991) find options increase prices in a mean-variance framework when investors differ on the variance of future prices and agree on expected values. Universal agreement on expected values seems a rather draconian assumption given profitable investment services such as Zack's Corporate Earnings Estimator and I/B/E/S that publicize the wide dispersion of published earnings and growth estimates.

In addition to papers that consider expansion of investors' opportunity set, a second tributary of literature typified by Stein (1987) and Back (1993) notes how options need not lead to more complete markets to affect security prices. Even where options are designed as the mathematically redundant securities contemplated by Black-Scholes, their existence may alter how information flows through the markets. Informed traders who once traded stocks may be drawn to the option market. Other speculators who never traded the stock may now do so if bid-ask spreads decline. Like the market completion models, the theorized effect that options produce in stock price levels is ambiguous in these models.

Given theorists' inability to establish what should happen to stock prices in response to option introductions, perhaps we should not be surprised that empirical resolution has been slow to develop. Early studies by Branch and Finnerty (1981),

Detemple and Jorion (1990), and Conrad (1989) disclose positive excess returns in narrow windows around call option introductions. However, an unpublished working paper by Damodaran and Lim (1991) finds negative effects for put introductions in the same time frame used by Conrad.

Sorescu (1997) provides the most current and exhaustive analysis of the impact of option introductions on stock price levels. His data set covers more years and more introductions than any previous study. While confirming the findings of previous authors, Sorescu demonstrates that the documented positive price response is limited to introduction years prior to 1981. Post-1980, option introductions, on average, have been accompanied by a negative stock price response. The truth of the adage "a picture's worth a thousand words" is demonstrated in Figure 2-1.

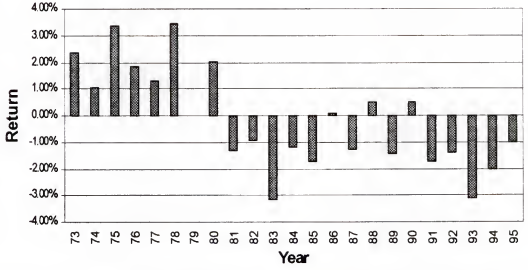

Figure 2-1. Mean 11-Day Cumulative Abnormal Return upon Option Introduction

Sorescu suggests the post-1980 stock price response portrayed in Figure 2-1 is the "true" effect of option introductions on stock prices. He observes pre-1981 observations may be tainted by stock price manipulation conducted by sophisticated option traders at

the expense of unsophisticated investors. Regulations designed to curb the use of options to manipulate markets were imposed by the Federal Reserve on August 11, 1980, and the shift in stock price response from positive to negative closely corresponds to this date.

Regardless of the impetus for mean positive abnormal returns prior to 1981, one must conclude that the last 15 years of option introductions are accompanied by significant average stock price declines. The consistency and persistence of these declines across many years leads to the search for a suitable theory to explain the phenomenon. Short-sale constraint relaxation is the hypothesis offered by this essay.

Short-sale Literature

Figlewski and Webb (1993) have documented a link between option trading and short selling. Specifically, they find optioned stocks are more heavily shorted than non-optioned stocks in general, option introductions coincide with increased short selling in the stock, and of significant importance to our analysis, they observe that short selling is positively and significantly (t=8.37) related to the difference in implied volatility between put and call option contracts. A large difference in put and call implied volatility suggests trading is being driven by simultaneous (though not necessarily coordinated) put buying and call writing.[2] Both of these strategies generate returns negatively correlated with

---

[2]Implied volatility is the volatility measure that equates the theorized price derived under a pricing model (e.g., Black-Scholes) with the observed price of the option. Since other parameters of the model (stock price, strike price, time to expiration, and interest rate) are observable, a specific implied volatility is required for the model's predicted price to equal the observed option price. Presumably, the implied volatility should reflect the market's assessment of future return variance, and a single implied volatility should exist for options that expire simultaneously assuming no asymetric jumps in stock prices. Differences in implied volatility suggest market participants are actually concerned with some characteristic unexplained by the pricing model and that the price disparity has not, or can not, be fully arbitraged despite sophisticated option trading programs designed to exploit relative mispricing across option contracts.

stock ownership. Figlewski and Webb suggest put buying and call writing are "transformed into an actual short-sale by a market professional who faces the lowest cost and fewest constraints."

The Figlewski-Webb results are consistent with discoveries by Brent, Morse, and Stice (1990) who, using a cross-sectional regression of short interest on several variables, find a significantly positive coefficient attached to a dummy variable indicating the presence of exchange traded options. They also find a positive relationship between monthly changes in option open interest and changes in short interest levels of underlying stocks.

The presence of option related short selling suggests potential price level changes might be analyzed in the context of models that consider the impact of short-sale constraints. Three seminal works by Miller (1977), Jarrow (1980), and Diamond and Verrecchia (1987) model the impact of short-sale constraints and prohibitions on share prices.

Miller suggests numerous observed market behaviors can be explained by a downward sloping demand curve for individual securities. In the presence of short-sale constraints, he theorizes that the absence of pessimistic short sellers will result in enthusiastic buyers bidding up the price of a security to levels above that which average investors perceive as fair. Where disagreement exists over the expected market price of a security (i.e., the probability distribution of future prices), a market populated with risk neutral investors will pay more for assets that have the greatest divergence of opinion--the most informationally opaque (riskiest) securities. Miller contends that the elimination of short-sale restrictions results in an increased supply of stock as pessimists sell additional

shares to optimists. As pessimists drive the supply curve rightward, the valuation of the marginal shareholder declines, and the market price of the stock will fall.

Jarrow's more rigorous analysis seemingly rejects Miller's intuitively appealing observations. Given two markets, identical in all respects except that one prohibits short selling, Jarrow demonstrates that the price of an individual stock can either increase *or* decrease when short-sale restrictions are eliminated. To understand Jarrow's analysis consider a simplified market consisting of two stocks (A and B), which initially cannot be shorted. If market rules are changed to allow short sales, we cannot be sure the prices of both A and B will fall. Investors who are "bullish" on stock A may choose to short stock B and use the proceeds[3] to buy more of stock A. The supply of stock B will rise and B's share price will fall, as Miller predicts. However, the additional demand for A's shares increases A's share price. Jarrow recognizes "optimists" may use the short-sale market to finance assets for which they hold the most rosy view.

While Jarrow's results appear to be at odds with Miller's earlier findings, this is not actually the case. Miller examines the partial equilibrium effects of relaxing one stock's short-sale constraint while Jarrow models the general equilibrium impact of simultaneously eliminating all stocks' short-sale constraints. In Chapter 4, I produce a Jarrow-style general equilibrium model incorporating Miller-type assumptions. The resulting equilibrium price levels are then dissected to ascertain the relative magnitude of short-sale-restriction-induced overpricing.

Diamond and Verrecchia (1987) examine the effects of short-sale constraints on the speed with which security prices adjust to private information. They assert that short

[3]This assumes investors can receive the proceeds of short sales.

sellers are more likely to be informed due to the relatively higher costs of short selling. A cornerstone of Diamond and Verrecchia's model is an assumption that investors are rational Bayesian estimators. In this framework, "rational expectation formation changes the market dynamics and removes any upward bias to prices." Diamond and Verrecchia do not claim individual securities will reflect the information short sales might convey, but their model suggests that the market price of each stock will be an unbiased estimate of its value in a market free of short-sale constraints.

Thus, competing theoretical arguments regarding the impact of short-sale restrictions have yet to be resolved. Diamond and Verrecchia contend that short-sale constrained stocks have unbiased prices, and Miller argues that stock prices are upward biased. While Jarrow contends that the direction of bias is indeterminate for individual securities in the context of a total market transformation, I will provide a model in the spirit of Jarrow's analysis that supports Miller's theory. Such theoretical discord invites empirical investigation to weigh the evidence and document which effects prevail. To my knowledge, no previous paper empirically tests whether prices are upward biased as a result of the short-sale constraints at work in the stock market.

Papers Describing Demand Curves for Common Stock

An ancillary contribution of this paper is that it complements a small body of work documenting the presence of downward sloping demand curves for individual equity securities. Unless demand curves for individual securities are downward sloping, an increase in the supply of the stock will not affect the price. In this sense, empirical tests conducted in this paper are joint tests for sloped demand curves and for the hypothesized option-short-sale interactions. The slope of an individual stock's demand curve is a

subject of importance since financial theories often depend upon the assumption that demand curves are perfectly elastic. Modigiliani-Miller, simple cost of capital rules, CAPM, and other theories dependent on an efficient market assumption require horizontal or almost horizontal demand curves.

Previous studies documenting downward sloped demand curves fall into three classes--block trade studies, S&P 500 listing (and delisting) studies, and Bagwell's (1992) Dutch auction share repurchase study. This analysis provides a fourth classification. Among the numerous studies examining the effect of large block trades on security prices, a negative price reaction to sales and a positive price reaction to purchases is usually observed (Scholes 1972; Holthausen, Leftwich & Mayers 1987; Mikkelson & Partch 1985). These price movements may suggest either a downward sloping demand curve or a negative information release. Harris and Gurel (1986), Shleifer (1986), Goettzman and Garry (1986), Jain (1987), and Lynch and Mendenhall (1997) examine listings and delistings in the S&P 500. Their findings suggest a positive (negative) return on listing (delisting) resulting from a demand curve shift as money managers adjust portfolio allocations to track the S&P 500 index. Sloped demand curves are also evidenced in Bagwell's (1992) examination of Dutch auction share repurchases.

Since option introductions are known in advance, information effects associated with option listing (if any exist) should be associated with announcement rather than introduction. Therefore, like the S&P 500 listing papers, this dissertation offers the relatively rare opportunity to test for sloped demand curves free of contaminating "information" events. However, while the S&P 500 introduction produces additional demand for the stock as mutual funds add to their holdings, this dissertation advances the

theory that option listings shift the supply curve by allowing more sellers to transact. The shift in the supply curve reveals a segment of the demand schedule that previously existed but that was ex-ante unobservable. In other words, manifested demand has changed although the underlying demand may not. In this sense, an option introduction allows the elasticity of the demand curve to be examined while an S&P 500 listing does not.

CHAPTER 3
INSTITUTIONAL DETAILS CONNECTING OPTIONS AND MARKET MAKER SHORT SALES

Both Figlewski and Webb (1993) and Brent, Morse, and Stice (1990) document a relationship between option trading activities and short selling. These findings are consistent with several previously documented findings that suggest options markets interact with the stock market via short selling. Let us examine a few facts consistent with this assertion. First, market-wide short-sale interest has risen precipitously in the last 20 years. NYSE short interest as a fraction of total shares has risen from less than a tenth of one percent in 1977 to over 1.3% at 1995 year end (NYSE Fact Book 1995). This major increase in short selling coincides with establishment and expansion of exchange traded stock options.

In addition to a rise in the general level of short sales, the motivations for short selling appear to have evolved. Once short sales arose principally as a bet that a stock's price would fall. Specifically, McDonald and Baron (1973) cite a 1947 survey indicating two-thirds of short sales were for speculative purposes. In contrast, an article in Business Week comments "only a tiny fraction of short sales are bets on the direction of stocks. The vast majority--perhaps 98% by one informed estimate--are merely efforts to hedge stock holdings or take advantage of arbitrage opportunities with other forms of investment" ("Secret World," August 5, 1996, p. 64). Even if some would question

whether the magnitude is as high as 98%, the fact remains that short sales are much more likely to be a component of a sophisticated hedge today than in decades past.

One venue of arbitrage activities involving short sales, undoubtedly, is the options market. Exchange traded options will generate short sales when they are used either to reduce risk in an investor's stock position or to establish a "pseudo-short" position when direct short selling is more costly.[1] Both of these uses are likely to produce short sales by market makers because market makers must hedge the long option positions they assume in their role as counter-party to investors who are establishing short option positions. In the case of investor risk shifting, an investor who is long shares of firm XYZ may reduce exposure to loss by adding options to his portfolio. The most effective technique is to purchase put options on XYZ. When the stock price falls, the gain on puts offsets the stock loss. However, a put purchaser must pay a premium for such insurance. For the cash constrained, writing covered calls offers a less costly alternative. Unfortunately, the investor also enjoys less loss insurance when writing covered calls than from buying a put because a different payoff structure is produced. Writing covered calls offers some downside protection as it enhances the payoffs in all of the stock's bad states of nature at the cost of capping high-end returns. Of course, once an investor has written a call option, he is less cash constrained. Thus, brokers often encourage the use of "collars" in which writing calls funds the purchase of puts on the same stock. In the extreme, collars can be structured so that a long stock position is completely hedged and a stock sale has

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[1]Other motivations for short sales or option trade might include a desire to lock in gains while deferring taxes that are payable when an appreciated long position is sold. Such sales may be motivated by risk avoidance rather than general pessimism. Without regard to motivation, the effect of short-sale constraints are the same.

effectively occurred. Largely due to tax advantages, these arrangements became sufficiently pervasive, that Congress, via The Tax Relief Act of 1997, enacted legislation to alter the tax treatment of those collars that effectively produce a stock sale. The Treasury has been assigned the unenviable task of discerning how much risk reduction is allowed before a stock sale is deemed to have occurred.

Some investors have no desire to hedge their long stock positions. Instead, they truly wish to bet against the stock, and options can be used for this as well. Once again, the technique involves writing calls and/or buying puts. In effect, owning the stock can be considered the hedge position for a short position in the options. The most unabashed bears will short via naked option positions while the timid partially cover their option positions with a long stock.

Such strategies may drive Figlewski and Webb's findings that, on average, the implied volatility of put options exceeds the implied volatility of call options matched on strike price and expiration date. Assuming the underlying stock has a single "true" volatility, a higher implied volatility for a put than its matched call suggests the put is overpriced relative to the call since the price of both options rises with stock volatility. Presumably, higher put prices are the result of buyer driven trade while lower call prices result from seller initiated transactions. Thus, Figlewski and Webb suggest a disproportionate share of option activity results from investor order flow in the form of put purchases and call sales.

How do option market makers respond to investors' order flow? If investors are net buyers of puts and writers of calls as indicated by implied volatilities, it follows that market makers are net buyers of calls and writers of puts since the sum of all option

positions tautologically equals zero. However, option market makers may not wish to bear all risk that the investing public finds distasteful. We can expect market makers, in turn, to hedge their positions. Enter short sales.

Returning to the option market maker's portfolio problem, since the market maker's put sales and call purchases both pay off in a rising stock market, the market maker's option holdings offer no portfolio diversification advantages but entails high risk. To hedge the risks associated with holding naked options, market makers turn to the short sale[2]. Recall from put-call parity that the purchase of a call with the simultaneous sale of a put with an identical strike price can be converted into the sale of a bond via shorting one share of stock. Alternatively, Black-Scholes delta hedging can be accomplished in the absence of a matching put or call via a continuously rebalanced short position. Although transaction costs should allow put-call parity hedges to be less costly to implement than continuously rebalanced Black-Scholes delta hedges, both methods call for short sales by market makers.

Having considered market maker responses to hedging activities by long investors, let us return our attention to the short-sale-constrained investor who will be introduced in the forthcoming model. This investor holds negative views on XYZ's stock, but he cannot act on such views absent the options market. Upon introduction of exchange

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[2]This analysis can be expanded to consider an individual market maker's alternative strategy of hedging the initial transaction with other option trades rather than via a short sale. In this case, the party who contracts on the second transaction is left with risks and needs to hedge. Since option positions aggregate to zero, if investors' demand to write calls and sell puts exceeds investors' demand to buy calls and sell puts, the positions taken by market makers require a sale of the underlying stock unless the market makers are willing to assume the transferred risk. This observation is consistent with the story articulated above.

traded options, such an investor can craft a synthetic short position by buying puts and writing calls as described above. The market makers, oblivious to the motivations of the stock investor, write puts, buy calls, short XYZ stock, and sleep well knowing they are comfortably hedged (unless they delta hedge and never sleep).

Why might an investor be short-sale constrained prior to option introduction? The reasons are numerous and well articulated by Asquith and Muelbroek (1995). Among the reasons investors usually face high costs to short sell are the following:

1. Investors generally do not receive the proceeds of a short sale. Instead, the brokerage firm that loans the shares and executes the short sale retains the proceeds and earns interest on those proceeds as compensation for providing the loan. As a result, relative underperformance is not sufficient for the seller to earn profits, but an actual price decline is needed. If the investor received the proceeds of his short sale, he would invest those proceeds and earn a profit if the alternative investment outperformed the shorted security. When the alternative investment earns a sure zero return because the proceeds are retained by the brokerage, any stock price increase generates a sure loss to the short seller.
2. Since most stocks, even relatively "bad" ones, tend to rise in price given enough time, failure to receive sale proceeds forces most short sellers to transact with a relatively short investment horizon. Given that transaction costs must be amortized across the holding period, transaction costs have a greater impact on the returns realized by short sellers than most long investors. Hence, transactions costs reduce the number of desired short

positions that can be profitably implemented. In particular, high bid-ask spreads should erect a barrier to short selling.

3. SEC Rule 10a-1 imposes on the exchanges an "uptick" rule. Short sales cannot be executed at a price below the preceding transaction price. NASDAQ, while not subject to the SEC rule, contends the NYSE marketed itself to firms as offering better protection against short sellers. NASDAQ has responded to the perceived competitive disadvantage by implementing a similar (perhaps more restrictive) bid-to-bid rule effective September 6, 1994. The NASDAQ bid-to-bid rule restricts short selling when the current inside bid is lower than the previous inside bid. The intent of both rules is to restrict short sales when securities are most "vulnerable" to short-sale activity, that is, when these securities experience large price declines. Options market makers are not subject to the bid-to-bid restriction.
4. Regulation T requires a short seller to deposit 50% of the market value of the shorted shares as margin requirement although cash deposits are not required as long stock positions meet the requirement under most circumstances.
5. To short a stock, one must first find a willing lender. For firms that are less widely held, these search costs may be substantial. In the extreme, the stock may be unavailable.
6. Short squeezes can force premature liquidation on the short seller resulting in a loss that cannot be recouped unless replacement shares can be borrowed before the price falls as expected. A short squeeze might occur where a seller borrows and sells a stock that the owner/lender of the shares demands be

returned. Since the short seller is obligated to return the shares on demand, he may be forced to liquidate prematurely at a loss. To protect against this type of squeeze, short sellers frequently desire to know who owns the shares they borrow.

Given what may be prohibitively high costs of short selling, options provide high cost investors with an opportunity to establish a lower cost synthetic short position. The options market maker with the lowest cost of short selling a particular security executes a short sale to hedge his option position. By allowing the party with the lowest costs to execute the short-sale transaction, aggregate short sales increase,[3] and because market makers compete for business, increased market efficiency results as the benefits of market makers' lower short sale costs are passed to investors.

[3]This assumes demand curves are negatively sloped and that investors do not fully condition their demand on the ease of shorting a stock.

CHAPTER 4
A SIMPLE MODEL OF SHORT-SALE CONSTRAINTS WITH HETEROGENEOUS INVESTOR VALUATIONS

Introduction

In order to establish the effect on stock prices of an option listing, we turn our attention to the price effect created by short-sale restrictions on the subject stock. As discussed in Section 1, Jarrow (1980) produced a model of short-sale effects in the context of a market-wide prohibition of short sales. Jarrow concluded that global short-sale prohibitions would not raise all stock prices. Some stocks would rise while others fell if global constraints were eliminated.

Elimination of short-sale constraints globally (i.e., across all stocks) is not the environment produced by introduction of an equity option on a single stock. An option introduction allows each investor to create a synthetic short position in the underlying stock, but not in other stocks. Option market makers, as observed by Figlewski and Webb (1993), may act as the counter-party to investors holding synthetic short positions. These market makers, long in the option but desiring neutral potential payoffs, short the underlying stock as a hedge against their option position. The model presented in this chapter presumes that option market makers have lower relative costs of short selling than most investors. This presumption is supported by academic research (Figlewski and Webb) as well as by inquiry with CBOE market makers.

To analyze the effect of eliminating a single security's short-sale constraint, I produce a Jarrow-inspired model showing the impact of a short-sale restriction on the firm's stock price. The model predicts that a company's stock price will drop when the short-sale constraint on the firm is relaxed. Further, the model predicts both a firm's beta and the standard deviation of investors' expectations of the firm's future value are positively related to the degree of "overpricing," where overpricing is defined as the stock's price in excess of the price that would obtain without the binding constraint. The empirical implications are that high beta stocks with highly diverse investor expectations of future value will fall more when options are introduced than stocks with low betas and low dispersion of investor belief.

This section is divided into four subsections. The first introduces the assumptions on which the model is based. The second solves for equilibrium prices with and without the short-sale constraint on the stock of interest. The third derives cross-sectional comparative static predictions that can be tested empirically. And the forth provides a summary to this chapter.

Assumptions

To simplify the analysis and highlight salient results in our model, we assume the existence of two risky securities. One security is a stock for which short selling is not permitted. The other security represents the aggregate market for risky securities exclusive of the stock we have chosen to examine. The market security is presumed to be subject to no short-sale constraints, although our results do not depend on this assumption.

Several assumptions define the capital market that prices our two securities. These assumptions are as follows:

(A.1) Asset shares are infinitely divisible

(A.2) No taxes or transaction costs exist

(A.3) Market participants, of which there exists some large number k, are all price takers

(A.4) Asset returns are multivariate normal

(A.5) The riskless asset produces a zero return, and unrestricted borrowing and lending may occur at the riskless rate.

(A.6) Investors act at time zero (t=0) to maximize their expected utility of wealth at time one (t=1).

(A.7) Investors exhibit constant absolute risk aversion that Pratt (1964) shows is equivalent to $U^k(W(1)) = c_1 - c_2 e^{-aW(1)}$, where $c_1 > 0$, $c_2 > 0$ are constants and a>0 describes investor k's risk aversion.

Each of the seven enumerated assumptions are consistent with assumptions used by Jarrow. In aggregate, these assumptions fully describe how the market responds to investor beliefs. Next, we must describe the structure of investor beliefs to be impounded by the market into a common set of prices.

We assume investors agree on the variance-covariance matrix of stock and market prices at time t=1, and they agree on the expected future price of the market security as well. However, while considering all available information, investors disagree over the expected value of the stock at time t=1. The theme of this model is contained in the assumption of heterogeneous expectations, and an important implication is derived from

the dispersion of investor expectations.[1] To summarize, each investor has a different belief regarding the future realization of the stock price, but investors are identical in other features.

The Model

Our two risky assets, the stock and the market, have prices $P_S(t)$ and $P_M(t)$ respectively. The model begins at t=0 and ends at t=1. The riskless asset takes the value $P_O(0) = P_O(1) = 1$. In equilibrium, the k^{th} investor solves a constrained optimization of the form

$$\max_{\left(N_O^k, N_S^k, N_M^k\right)} E^k U^k\left(W^k(1)\right) \tag{1}$$

subject to

$$W^k(0) = N_S^k P_S(0) + N_M^k P_M(0) + N_O^k P_O(0)$$

$$N_S^k \geq 0$$

Each investor maximizes his expected utility with respect to time 1 wealth, $W^k(1)$. The superscripts on the utility function and on the expectations operator denote that each investor has his own beliefs and utility function. The demands for individual assets are denoted as N_S^k (stock), N_M^k (the market) and N_O^k (the riskless asset), while initial wealth, which is exogenously determined, constrains the investor's portfolio selection choices. $N_S^k \geq 0$ denotes the short-sale constraint.

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[1]The available information considered by each investor prior to t=0 can include the current stock price. The model only requires that individual investors continue to value their own private information. Each investor must not believe the current stock price accurately subsumes all information including his own but must believe that his private information continues to provide some small profit opportunity.

Lintner (1969) shows the exponential utility function we have assumed, in combination with normal returns, conveniently collapses to a form that may be solved as

$$\max_{(N_O^k,\ N_S^k,\ N_M^k)} N_S^k E^k P_S(1) + N_M^k E^k P_M(1) + N_O^k - \left(\frac{a^k}{2}(N_S^k)^2 \sigma_{SS} + \frac{a^k}{2}(N_M^k)^2 \sigma_{MM} + a^k N_S^k N_M^k \sigma_{MS} \right) \tag{2}$$

subject to

$$W^k(0) = N_S^k P_S(0) + N_M^k P_M(0) + N_O^k P_O(0)$$
$$N_S^k \geq 0$$

where the variance-covariance matrix of t=1 stock and market prices takes the form

$$\Omega^k = \begin{bmatrix} \sigma_{MM} & \sigma_{MS} \\ \sigma_{MS} & \sigma_{SS} \end{bmatrix} \tag{3}$$

The Lagrangian of (2) is given by

$$\begin{aligned} L = {} & N_S^k E^k P_S(1) + N_M^k E^k P_M(1) + N_O^k \\ & - \frac{a^k}{2}\left[(N_S^k)^2 \sigma_{SS} + (N_M^k)^2 \sigma_{MM} + 2 N_S^k N_M^k \sigma_{MS} \right] \\ & + \lambda_W^k \left(W^k(0) - N_S^k P_S(0) - N_M^k P_M(0) - N_O^k P_O(0) \right) \\ & + \lambda_S^k \left(N_S^k - S_S^k \right) \end{aligned} \tag{4}$$

where λ_W^k and λ_S^k and are non-negative Lagrangian multipliers for the wealth and short-sale constraints respectively, and S_S^k is a non-negative slack variable with the property that $\lambda_S^k S_S^k = 0$.

Differentiating with respect to $\lambda_W^k, \lambda_S^k, N_S^k, N_M^k, N_O^k$, first order conditions derived from (4) are

$$W^k(0) - N_S^k P_S(0) - N_M^k P_M(0) - N_O^k P_O(0) = 0 \tag{5}$$

$$N_S^k \lambda_S^k = 0, \quad \lambda_S^k \geq 0, \quad N_S^k \geq 0 \tag{6}$$

$$E^k P_S(1) - P_S(0)/P_O(0) + \lambda_S^k = a^k N_S^k \sigma_{SS} + a^k N_M^k \sigma_{MS} \tag{7}$$

$$E^k P_M(1) - P_M(0)/P_O(0) = a^k N_S^k \sigma_{MS} + a^k N_M^k \sigma_{MM} \tag{8}$$

$$\lambda_W^k = 1 / P_O(0) \tag{9}$$

The wealth constraint expressed by equation (5) must be binding by virtue of $\lambda_W^k > 0$ per equation (9). Standard Kuhn-Tucker conditions comprise expression (6). Where the short-sale constraint binds, $\lambda_S^k > 0, N_S^k = 0$ holds, and when the short-sale constraint is non-binding $N_S^k > 0$ and $\lambda_S^k = 0$. Trivially, $N_S^k = 0$ may be the optimal demand for the stock without the short-sale constraint and $N_S^k = 0$, $\lambda_S^k = 0$ is technically feasible. This exhausts all possible combinations.

Equations 7 and 8 can be solved for N_M^k and N_S^k with the result

$$N_M^k = \frac{1}{a^k}\left[\left(\frac{\sigma_{SS}}{D}\right)\left(E^k P_M(1) - \frac{P_M(0)}{P_O(0)}\right) - \left(\frac{\sigma_{MS}}{D}\right)\left(E^k P_S(1) - \frac{P_S(0)}{P_O(0)}\right)\right] - \left(\frac{\sigma_{MS}}{D}\right)\lambda_S^k \tag{10}$$

$$N_S^k = \frac{1}{a^k}\left[\left(\frac{\sigma_{MM}}{D}\right)\left(E^k P_S(1) - \frac{P_S(0)}{P_O(0)}\right) - \left(\frac{\sigma_{MS}}{D}\right)\left(E^k P_M(1) - \frac{P_M(0)}{P_O(0)}\right)\right] + \left(\frac{\sigma_{MM}}{D}\right)\lambda_S^k \tag{11}$$

where

$$D = \sigma_{SS}\sigma_{MM} - \sigma_{MS}^2 > 0$$

Equation 11 provides an insight that foreshadows future findings. Notice that the demand of the k^{th} investor for the stock can be divided into two parts. The left-hand term describes the stock demand when short-sale constraints do not apply. The right-hand term, $\frac{\sigma_{MM}}{D}\lambda_S^k$, is the additional demand component created by the short-sale constraint. If the constraint is non-binding, $\lambda_S^k = 0$, and the second term dissolves. However, when the constraint binds, the right-hand term is always positive. Thus, given equilibrium asset prices, every investor's demand for the stock is weakly higher when a short-sale constraint is in place.

The next step in completing the market equilibrium description is to aggregate all individual investor demands defined by equations (10) and (11) and equate these demands to the supply of those assets (Q_S and Q_M).

$$Q_S \equiv \sum_k \frac{1}{a_k}\left[\left(\frac{\sigma_{MM}}{D}\right)\left(E^k P_S(1) - \frac{P_S(0)}{P_O(0)}\right) - \left(\frac{\sigma_{MS}}{D}\right)\left(E^k P_M(1) - \frac{P_M(0)}{P_O(0)}\right) + \left(\frac{\sigma_{MM}}{D}\right)\lambda_S^k\right] \quad (12)$$

$$Q_M \equiv \sum_k \frac{1}{a_k}\left[\left(\frac{\sigma_{SS}}{D}\right)\left(E^k P_M(1) - \frac{P_M(0)}{P_O(0)}\right) - \left(\frac{\sigma_{MS}}{D}\right)\left(E^k P_S(1) - \frac{P_S(0)}{P_O(0)}\right) - \left(\frac{\sigma_{MS}}{D}\right)\lambda_S^k\right] \quad (13)$$

Notice from equation (12) that the aggregate demand for the stock is composed of three terms. The first two terms are the unconstrained demand for the stock. The last term, $\sum_k \frac{\sigma_{MM}}{D}\lambda_S^k$, is a value that must always be non-negative and represents the additional demand for the stock that arises from the short-sale constraint.

Because we have two unknowns $\left[\frac{P_S(0)}{P_O(0)}, \frac{P_M(0)}{P_O(0)}\right]$ and two equations, we can solve for the time t=0 prices of the stock and market relative to the price of the riskless security. Before doing so, let's review a few simplifying assumptions that enhance computational ease. First, since the riskless rate is zero, $P_O(0) = P_O(1) = 1$. Likewise, recall all investors are assumed to possess the same expected value of the market security's price, $E^k P_M(1)$. Now, also assume that all investors are equally risk averse such that $a^k = a = 1$, $\forall k$. Using these assumptions our market clearing prices become

$$P_S = \left[\frac{\sum_k E^k P_S(1)}{k}\right] - \left[\frac{Q_S\sigma_{SS} + Q_M\sigma_{MS}}{k}\right] + \left[\frac{\sum_k \lambda_S^k}{k}\right] \quad (14)$$

$$P_M = EP_M(1) - \left[\frac{Q_M\sigma_{MM} + Q_S\sigma_{MS}}{k}\right] \quad (15)$$

Conveniently, the price of the stock, P_S, is the sum of three terms. The first term is the mean estimate of future value by all investors. Recall that the riskless rate is zero. Absent a risk component, the mean projected return on the stock would be zero. The second term, normally a reduction in P_S, takes account of the variance and covariance risks that the stock investment entails.[2] Finally, the third term is a price increase composed of the sum of all investors' short-sale constraints. Notice that this term must be non-negative. The increase in the equilibrium price that the short-sale constraint creates is embodied in the third term. It is this term that we must examine further to gain insights on the nature of the relative overpricing. In the next section we will turn to an analysis of comparative statics on $\sum_k \frac{\lambda_S^k}{k}$.

Evaluating the Short-sale Constraint Overpricing Term

Having determined in the prior section that short-sale constraints raise the equilibrium price of a security, we turn our attention to the factors that control the magnitude of the upward bias. To examine the third term of equation (14) in greater detail, observe that for any investor

$$\lambda_S^k = \max\left[0, \left(\frac{\sigma_{MS}}{\sigma_{MM}}\right)\left(EP_M(1) - P_M(0)\right) - \left(E^k P_S(1) - P_S(0)\right)\right] \tag{16}$$

Equation (16) follows from equations (11) and (6). For investors who are not short-sale constrained, $\lambda_S^k = 0$. Investors who are short sale constrained have demand $N_S^k = 0$ with $\lambda_S^k = \left(\frac{\sigma_{MS}}{\sigma_{MM}}\left(E^k P_M(1) - P_M(0)\right) - \left(E^k P_S(1) - P_S(0)\right)\right)$ from equation (11).

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[2]This second term can increase the stock price when the stock's covariance with the market is negative.

Using equation (16), the effects of a stock's beta on its level of price bias can be observed with ease. For any individual

$$d\lambda^k/d\beta \geq 0 \text{ where } \beta = \sigma_{MS}/\sigma_{MM} \tag{17}$$

Since the mean value of all λ_S^k terms is the aggregate price effect of the short-sale constraints, it follows that the upward price bias is positively related to the stock's beta if even one investor is short-sale constrained. The intuition behind investors' preference to short high beta stocks is relatively straightforward. Investors reduce portfolio risk as they remove high beta firms from their holdings. Even after a high beta firm has been eliminated from the portfolio, the portfolio's risk can be further reduced by shorting the stock. In other words, shorting a high beta stock in an otherwise long portfolio will reduce the portfolio's risk more than shorting a low beta firm.

Beta is not the only factor affecting the level of price bias. Looking at equation (16) we see that the investor's expected return on a stock investment, $[E^kP_S(1) - P_S(0)]$, affects an investor's level of short-sale constraint. This is an intuitive result since a very low expected price at time t=1 should induce a greater desire to sell short. The intuition is born out as $d\lambda^k/dE^kP_S(1) = 1$. Unfortunately, since not every investor possesses the same $E^kP_S(1)$, we cannot simply sum the individual constraints and hope to learn much about the combined impact of investors' stock return expectations.

Intuition suggests the that level of price bias should be related to the degree by which investor expectations differ. A stock that has large optimistic and large pessimistic followings will, in the presence of short-sale constraints, see its price bid up as optimists

compete for a fixed supply of the stock. Without the short-sale constraint, the pessimists would compete amongst themselves to sell large quantities to the optimists, driving down the price. Obviously, overpricing is dependent upon optimists' inability to fully adjust their beliefs based upon the predictable bias. To see what our model reveals about the impact of the dispersion of opinion on the stock price, assume that k is sufficiently large so that in the limit to a continuum $\frac{\sum_k \lambda_S^k}{k}$ takes the form

$$G = \frac{1}{k} \int_{-\infty}^{A+P_S(0)} \lambda_S [k\phi(EP_S(1))] dEP_S(1) \tag{18}$$

where $A = (\sigma_{MS}/\sigma_{MM})(EP_M(1) - P_M(0))$ and $[k\phi(EP_S(1))]dEP_S(1)$ is the number of investors in a small interval on the density function ϕ.

The upper limit of integration is derived from the observation $\lambda_S = 0$ for values of $EP_S(1) > A + P_S(0)$. See equation (16). Notice from Figure 4-1, optimists with high expectations for $P_S(1)$ do not impact the value of G, our continuous version of the price bias term. The intuition behind this observation is simple. Investors with high expected future values for the stock are not short-sale constrained. For them, $\lambda_S = 0$. Only those investors with low expectations face the constraint, and the lower each investor's expectation, the more constrained he becomes.

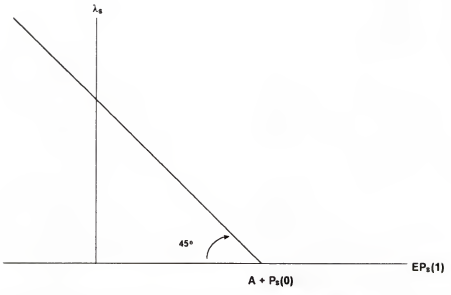

Figure 4-1. Lambda as a Function of Stock Price Expectations

For analysis, let us choose the uniform distribution to represent the destiny function $\phi(EP_S(1))$. Formally,

$$\phi(EP_S(1)) = \begin{cases} \dfrac{1}{\theta_2 - \theta_1}, & \theta_2 \geq EP_S(1) \geq \theta_1 \\ 0, & \textit{elsewhere} \end{cases}$$

For simplicity, I allow $\theta_1 = \mu + \theta$ and $\theta_2 = \mu - \theta$ where μ is the mean value of the distribution and θ is the "spread." This uniform distribution has the attractive feature that the variance of the distribution is independent of the mean value. In other words, the dispersion of investor expectations is measured by θ, and this dispersion variable can be altered without affecting the mean investor valuation assessment. Our objective is to derive a value for $dG/d\theta$ to determine how dispersion of investor expectations affects the magnitude of the upward price bias.

One might criticize the selection of the uniform distribution on grounds that it does not reflect realism. Perhaps the tails of the distribution should thin so that extreme optimism or pessimism is observed among relatively fewer investors. A normal distribution would possess this characteristic and would still allow for independence between the mean and variance of the distribution. However, the normal distribution also suffers a departure from reality in that corporate limited liability ensures that $EP_S(1)$ cannot take values less than zero. In any event, many of the results that follow have been reproduced using a normal distribution assumption, and I suspect that all other qualitative findings can be derived for the normal distribution as well.

By inserting into Equation 18 the appropriate non-zero values for λ_S with the uniform density function, we obtain

$$G = \int_{\mu-\Theta}^{A+P_S(0)} (A + P_S(0) - EP_S(1))(2\theta)^{-1}\, dEP_S(1) \tag{19}$$

which when evaluated over the limits of integration can be written as

$$G = (4\theta)^{-1}(A + P_S(0) - \mu + \theta)^2 \tag{20}$$

It follows that

$$\frac{dG}{d\theta} = -(4\theta)^{-2}4(A + P_S(0) - \mu + \theta)^2 + 2(4\theta)^{-1}(A + P_S(0) - \mu + \theta) \tag{21}$$

This derivative can be signed as $dG/d\theta > 0$ because $2\theta > A + P_S(0) - \mu + \theta > 0$. Recall that $\mu - \theta$ is the lowest possible investor valuation of $EP_S(1)$ while $A + P_S(0)$ is the $EP_S(1)$ valuation of an investor who chooses to hold zero shares. Thus, if any investor wishes to

sell short $dG/d\theta > 0$, and overpricing of the stock will increase when the dispersion of investor expectations, as described by the variance of a uniform distribution, rises.

We have now observed three implications from this model.

- Short-sale constrained stocks have prices biased upward.
- The degree of upward bias is greater for high beta stocks.
- Wider dispersion of investor beliefs generates higher bias

  (i.e. higher equilibrium stock prices).

Next, I derive results for the effect on the change in short interest when the short-sale constraint is relaxed. Specifically, I show that short interest increases in the stock's beta and dispersion of expectations as described by θ.

Return to Figure 4-1 where I have shown that upon the release of the short-sale constraint, all investors with valuations of $EP_S(1)$ below $A + P_S(0)$ will choose to short the stock. These investors will hold, in aggregate, S shares where

$$S = \int_{\mu-\Theta}^{A+P_S(0)} N_S\left(EP_S(1)\right)\left[k\phi\left(EP_S(1)\right)\right] dEP_S(1) \tag{22}$$

Recall that $N_S(EP_S(1))$ is the number of shares sold short by each investor, and $k\phi(EP_S(1))dEP_S(1)$ is the number of investors on any small interval of the density function ϕ. Notice that S is a negative value so that as S becomes smaller the level of short interest is increasing.

Once short sales are allowed, each investor's stock holdings are described by

$$N_S\left(EP_S(1)\right) = \frac{\sigma_{MI}}{D}\left(EP_S(1) - P_S(0)\right) - \frac{\sigma_{MS}}{D}\left(EP_M(1) - P_M(0)\right) \tag{23}$$

which is the unconstrained version of Equation 11 where $D = \sigma_{MM}\sigma_{SS} - \sigma_{MS}^2$. In combination with our uniform distribution assumption, the level of short sales is written as

$$S = \left(\frac{k}{D}\right)\left(\frac{1}{2\theta}\right)\left[\int_{\mu-\theta}^{A+P_S(0)} \sigma_{MM}\left(EP_S(1) - P_S(0)\right)dEP_S(1) - \int_{\mu-\theta}^{A+P_S(0)} \sigma_{MS}\left(EP_M(1) - P_M(0)\right)dEP_S(1)\right] \quad (24)$$

which, when evaluated and simplified, becomes

$$S = \frac{-k}{4\left(\sigma_{MM}\sigma_{SS} - \sigma_{MS}^2\right)\theta\sigma_{MM}}\left[\sigma_{MS}\left(EP_M(1) - P_M(0)\right) - \sigma_{MM}\left(\mu - \theta - P_S(0)\right)\right]^2 \quad (25)$$

This value for the constraint-free short interest level can be differentiated with respect to θ with the following results:

$$\frac{dS}{d\theta} = \left(\frac{k\sigma_{MM}}{4D\theta^2}\right)\left[\frac{\sigma_{MS}}{\sigma_{MM}}\left(EP_M(1) - P_M(0)\right) - \left(\mu - \theta - P_S(0)\right)\right] \times \left[\frac{\sigma_{MS}}{\sigma_{MM}}\left(EP_M(1) - P_M(0)\right) - \left(\mu + \theta - P_S(0)\right)\right] \quad (26)$$

This expression can be signed once one recognizes that $\mu - \theta$ and $\mu + \theta$ are the stock value expectations for the most pessimistic and optimistic investors, respectively. Therefore $\mu - \theta - P_S(0) < 0$ is the expected return on a long position for the most pessimistic investor while $\mu + \theta - P_S(0) > 0$ is the expected return for the extreme optimist. Since the most optimistic investor expects a return on the stock in excess of the market model return of $\frac{\sigma_{MS}}{\sigma_{MM}}\left(EP_M(1)\right) - P_M(0))$ we conclude that the expression in Equation 26 must be negative. Therefore, short interest increases as dispersion of expectations increases (ie. $dS/d\theta < 0$).

Next, let us turn our attention to the short interest level as a function of beta. Assuming σ_{MM} is constant, we can differentiate S with respect to σ_{MS} to discover the relationship between beta and short sales. Because the solution is not concise, let us restate S as

$$S = UV^2 \tag{27}$$

$$U = \frac{-k}{4\left(\sigma_{MM}\sigma_{SS} - \sigma_{MS}^2\right)\theta\sigma_{MM}} \quad < 0 \tag{28}$$

$$V^2 = \left[\sigma_{MS}\left(EP_M(1) - P_M(0)\right) - \sigma_{MM}\left(\mu - \theta - P_S(0)\right)\right]^2 \quad > \quad 0 \tag{29}$$

Also observe $V > 0$ from the previous discussion. Differentiating U and V^2 with respect to σ_{MS} yields the following two equations that are signed under the $\sigma_{MS} > 0$ assumption

$$\frac{dU}{d\sigma_{MS}} = \frac{-k\sigma_{MS}}{2\left(\sigma_{MM}\sigma_{SS} - \sigma_{MS}^2\right)^2\theta\sigma_{MM}} \quad < \quad 0 \tag{30}$$

$$\frac{dV^2}{d\sigma_{MS}} = 2V\left(EP_M(1) - P_M(0)\right) \quad > \quad 0 \tag{31}$$

In combination,

$$\frac{dS}{d\sigma_{MS}} = V^2\frac{dU}{d\sigma_{MS}} \quad + \quad U\frac{dV^2}{d\sigma_{MS}} \quad < \quad 0 \tag{32}$$

so that S falls and short interest rises as beta increases.

I have now solved for the effects of dispersion of expectations and beta on the share value overpricing $\left(\frac{dG}{d\theta} > 0, \frac{dG}{d\sigma_{MS}} > 0\right)$ and on unconstrained short interest levels $\left(\frac{dS}{d\theta} < 0, \frac{dS}{d\sigma_{MS}} < 0\right)$. Moreover, we can also observe from these results the relationship

between that the ex-ante overpricing of the stock and the ex-post unconstrained level of short interest must be $\frac{dG}{dS} < 0$. In other words, after the short-sale constraint on a stock has been removed, the price of the stock will drop more when the increase in short interest is greatest.

Empirical Implications

I now turn from the theoretical effects of short-sale constraints and their removal to empirical implications for option introduction events. To the extent that option introductions relax short-sale constraints on a stock, the preceeding model provides several testable hypotheses that are summarized as follows:

- Stock prices will decline (from $G>0$).
- High beta stocks will decline more than low beta stocks (from $dG/d\sigma_{MS}>0$)
- High dispersion of expectation stocks will decline most (from $dG/d\theta>0$)
- High beta stocks will have greater increases in short interest (from $dS/d\sigma_{MS}<0$)
- High dispersion of expectations stock will have greater increases in short interest (from $dS/d\theta<0$)
- The stocks that produce the largest increases in short interest will also evidence the largest price declines (from $\frac{dG}{dS} < 0$). Each of these hypotheses is tested in the following chapter.

CHAPTER 5
EMPIRICAL TESTS OF DEMAND CURVE DETERMINANTS

Introduction

The previous chapters have established the theoretical link between option introductions, short-sale increases, and share price declines. This chapter provides empirical evidence that both option window abnormal returns and changes in short interest levels are related to a stock's short interest demand determinants (i.e., a stock's beta and proxies for dispersion of investor expectations) as predicted by the model in Chapter 4. Moreover, in support of the model's contention that price changes are correlated with the equilibrium level of short interest, I find a significant negative correlation between the option window abnormal returns and the change in the level of relative short interest. Other evidence points convincingly to a strong relationship between the cross-sectional differences in the short interest level of stocks in the sample and both the systematic risk and unsystematic risk demand factors even before the option is introduced. This relationship conforms to the predictions of the Chapter 4 model because, in reality, short sales are not prohibited prior to the option introduction. They are merely more costly to execute than after the option listing. Therefore, given the lack of a short-sale prohibition prior to option listing, the model would predict that pre-listing stocks should be more heavily shorted when they have high betas and high valuation disagreement across investors.

Before turning to the contents of this chapter, we should discuss the overarching organization of both this chapter and the chapter that follows. In one sense, Chapter 6 is a logical extension from this chapter. However, one can also view this chapter as a special case of the empirical model more fully developed in Chapter 6. In order to better understand the rationale for the division between these two chapters, I must digress for a moment. Hopefully this digression will also give the reader a new perspective on the material discussed before.

Consider in Figure 5-1 that observed short interest and the stock price describe an equilibrium reflecting both the demand for shares (long positions) and the supply of shares available (computed as issued shares plus short sales). The company has issued Q_I initial shares, but as the price rises some parties wish to short the stock giving rise to supply curve S. Given demand curve D, an equilibrium level of long positions (Q_L) will equal the sum of the initially issued shares and the shares sold short ($Q_L = Q_I+Q_S$). The equilibrium price is denoted as P.

However, short sales are more costly to execute than long positions. This cost is represented by C_S (the cost to short) in the chart. Because short sellers must pay C_S, they are no longer willing to supply shares along S, but will only supply S′ at any given price. Given the C_S cost of short selling, a new equilibrium is derived at E′ with a new price P′>P and a new short interest level $Q_S'<Q_S$. When options are introduced, the new securities ameliorate the costs of short selling so that C_S is eliminated, or at least lessened.

By redefining C_S as that portion of the cost mitigated by the option introduction, we will observe an abnormal return of (P-P′) and an increase in short sales of (Q_S-Q_S') upon option listing. Notice that as C_S increases, the overpricing increases and fewer

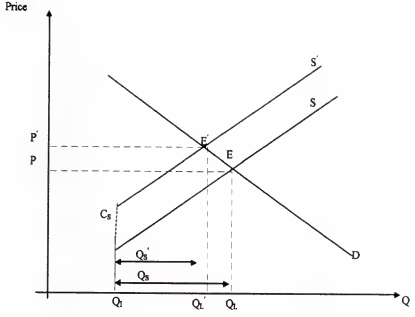

Figure 5-1. Graphical Representation of Short-sale Constraint Effects

shares are sold short. This suggests that the degree by which option listings reduce share price and increase short interest is dependent upon how much of C_S is eliminated.

It seems naive to believe that the degree to which options reduce the costs of short selling is cross-sectionally identical over all firms. In other words, the value of C_S in Figure 5-1 obviously is not identical for all listings. The magnitude of C_S will differ from company to company.

Nevertheless, in Chapter 5, I proceed with empirical tests under the assumption that C_S is constant, but I relax this assumption in Chapter 6. I have chosen to postpone consideration of the cross-sectional differences in constraint reduction until Chapter 6 for two reasons. First, holding the degree of constraint relaxation constant allows us to more narrowly focus on the impact of the factors that the Chapter 4 model has identified as relevant to the degree of mispricing. In other words, our empirical tests in this chapter will more closely conform to the model if we withhold consideration of cross-sectional

constraint differences. Second, the proxies that I will use for firm betas and for the dispersion of expectations have stronger support in existing literature than the proxies of constraint relaxation that are considered in Chapter 6. Interacting a poor proxy for constraint relaxation with the factors identified in the model could mask a relationship that otherwise would be obvious. Before turning to the tests performed in this chapter, I will discuss the data used and the alternative abnormal return metrics considered.

Data and Summary Statistics

Option introduction data has been provided by the Chicago Board Options Exchange. The listing dates used in this study are identical to those utilized in Sorescu (1997). Data for pre-1993 introductions were graciously provided by Sorin Sorescu. These pre-1993 data include 1236 listing events categorized as call-only or put-call joint listings. Put-only listings are not considered in this paper because they are always preceded by a call-only listing. Data for option introductions from 1993 to 1995 were obtained directly from the CBOE and provided to Sorescu for inclusion in his paper. All of these option introductions are put-call joint listings. The final data set contains 1946 listings.

As previously noted, a significant shift of return regimes occurs in late 1980. The focus of the empirical analysis in this paper will be on the post-1980 option introductions with pre-1981 listings reserved for subsequent analysis. The data set contains 259 pre-1981 introductions leaving 1687 introductions after 1980.

From this set of option introductions, I exclude several from my analysis because they fail to meet all of my inclusion criteria. Specifically, firms with stock splits occurring within a sixty trading day window around the event date (t-30 and t+30) have been eliminated from the analysis as short interest data may not be comparable from month to

month. Therefore, none of the regression results presented include observations that are "split-contaminated." Adjusting for splits is problematic because it can be difficult to determine whether splits occurring near the 7th of the month have been accounted for in the short interest data reported. In any event, splits are known to produce positive abnormal returns both around the split announcement and after the split date. See Ikenberry, Rankine and Stice (1996). Without adjusting for these abnormal returns, splits would contaminate our sample. Eleven firms "paid" stock dividends in the sixty day window around the event date. These firms were excluded from the sample as well.

In addition to splits, ADR's and foreign companies have been excluded from the analysis as activities in a foreign stock or option market may mute or contaminate the effects observed in the US markets. For example, if options are already trading on a foreign option exchange, we might not expect any effects from option introduction in the US market. Alternatively, US option introduction might spark short sales in a foreign market that we cannot observe with our data sources.

I have made no attempt to identify instances of US firms trading on foreign markets or short sales in those markets. An argument might be made for excluding such firms using the rationale employed to exclude foreign firms from the sample. However, I expect we would find very few firms listed on foreign exchanges around their option introduction date. The firms likely to be jointly listed on a foreign market are very large companies. Most of these firms had options listed in the 1970's when foreign listing of US firms was uncommon.

Most of the excluded firms were identified using data gathered from CRSP. CRSP data has been utilized extensively to gather return, price, volume, market capitalization,

and exchange data as well as NMS bid-ask-quotes, ADR identifiers, and stock split/dividend information.

For the set of firms that remain after excluding foreign firms and those with stock splits near the listing date, Table 5-1, Panel A provides a summary of annual option introductions and cumulative abnormal returns ("CAR" computed using Brown and Warner's market model) with the 6-day cumulative abnormal return measured from the listing date to 5 days beyond the listing date. The 11-day cumulative abnormal return is centered on the option introduction date. The alphas and betas used in the CARs are computed using stock and market return data from days t-100 to t-6 where t is the date of option introduction. These cumulative abnormal returns are computed as follows:

$$\text{BWCAR11} = \sum_{t=-5}^{5}\left(R_{it} - \hat{\alpha} - \hat{\beta}R_{Mt}\right)$$

$$\text{BWCAR6} = \sum_{t=0}^{5}\left(R_{it} - \hat{\alpha} - \hat{\beta}R_{Mt}\right)$$

BWCAR11 is the abnormal return measure used by Sorescu (1997), Conrad (1989), and other papers that examine returns around option listing dates. However, if abnormal returns are produced because a short-sale constraint has been removed, BWCAR6 would seem to be a more appropriate abnormal return measure than BWCAR11 since we have no reason to think that the constraint is removed prior to the option listing. On the other hand, since the date of an impending option introduction is not kept secret from potential customers or other interested parties, it seems likely that the abnormal returns documented by Sorescu will evidence themselves, at least in part, as the introduction date approaches. If so, BWCAR11 is likely to present a better measure of the level of abnormal return.

Observe in Table 5-1, Panel A that the mean Post-1980 BWCAR11 is approximately twice the mean of the BWCAR6 measure with a higher t-statistic as well. We infer some of the abnormal return occurs in days t-5 to t-1. Also, notice the dichotomy between Pre-1981 and post-1980 abnormal returns as discussed in detail by Sorescu.

Although the Brown and Warner abnormal return measure has been used in previous studies, at least two facts suggest that an alternative measure may be more appropriate. First, I observe that the stocks on which options are introduced are not "normal" in the sense that they have often had substantial price increases in the months immediately preceding the option introduction date. This price increase is manifested partly as a positive alpha in the estimation window. Of course, the average firm in the market must have a zero alpha, and we attribute the observed positive alpha values in the sample to a selection bias produced by the option exchanges' choice criteria. However, unless positive alpha values persist through time, one might reasonably assume a zero-alpha CAR measure will produce unbiased CAR values. As an alternative to the BWCAR11 and BWCAR6 measures, I also offer the following abnormal return metrics:

$$\text{NOALPH11} = \sum_{t=-5}^{5}\left(R_{it} - \hat{\beta}R_{Mt}\right)$$

$$\text{NOALPH 6} = \sum_{t=0}^{5}\left(R_{it} - \hat{\beta}R_{Mt}\right)$$

In addition to the selection bias possibly producing inappropriately high positive alpha values, the compounding of volatile daily returns also adds noise to the estimation period beta. Therefore, as an alternative measure of abnormal returns, I use the following two metrics:

$$\text{ABRET11} = \sum_{t=-5}^{5}(R_{it}) - \sum_{t=-5}^{5}(R_{Mt})$$

$$\text{ABRET6} = \sum_{t=0}^{5}(R_{it}) - \sum_{t=0}^{5}(R_{Mt})$$

Panels B and C of Table 5-1 report yearly mean values for each of the alternative abnormal return measures. Notice that these measures produce higher mean abnormal returns than BWCAR11 and BWCAR6 had evidenced. In fact, using this measure, there is no evidence of post-1980 abnormal underperformance. We will observe later that the cross-sectional differences in performance can be explained in some measure by the excluded alpha term not in the ABRET and NOALPH computations. This suggests that the "true" abnormal return would include a deduction of some positive fraction of the estimation period alpha rather than the zero-alpha assumptions imposed by the NOALPH and ABRET measures. Fortunately, this paper endeavors to explain cross-sectional differences in returns rather than divine the correct abnormal return measure. Moreover, after controlling for alpha as an explanatory variable, my results are reasonably robust to the abnormal return computation method.

Table 5-2 presents data on Cumulative Abnormal Returns (using the Brown and Warner metrics) in a series of six panels. These panels divide the universe of option introductions between call-only listings and put-call joint listings as well as by the trading venue of the underlying stock. Each panel reports the mean CAR for options introduced prior to 1981 and for options listed after 1980.

All panels indicate that post-1980 option introductions are accompanied by negative and statistically significant CARs while pre-1981 introductions produced positive

abnormal returns. This phenomenon occurred without regard to the type of listing (call-only vs. joint) or trading venue of the underlying stock.

Turning from our discussion of the abnormal return measures to the measurement of changes in short interest, I have collected short interest data for a four month window surrounding each option introduction event. Since short interest information is reported monthly, complete short interest data for any event consists of 4 data points. The analysis window begins with the short interest observation for the month preceding the month in which the listing event occurs and includes the short interest observation for the event month and the two succeeding months.

Short interest data have been obtained from the New York Stock Exchange and the NASD for recent years and from the Wall Street Journal, Barrons, and Standard and Poors Daily Stock Price Record for earlier years. All American Stock Exchange short-sale data were obtained from Standard and Poors Daily Stock Price Record. NASDAQ did not begin to report short interest until 1986, but only 40 NASD firms had listed options prior to the first NASD short interest reports. In addition, 10 firms with option listings after December 1, 1995 do not have sufficiently complete short interest data as my short-sale data is collected through December 1995 only.

Summary information on changes in reported short interest is provided in Tables 5-3, 5-4, and 5-5. Table 5-3 provides descriptive statistics on the two month change in short interest relative to shares outstanding ("ΔRSI") for each year from 1973 to 1995. Notice that the median change in short interest is positive for every year except 1981 and 1983, both of which have few observations. While the increase in short interest has become more pronounced in the 1990s, both mean and median short interest changes around option introductions were positive even in the 1970s.

Data from Tables 5-1 and 5-3 are combined in Figure 5-2. This chart suggests that after 1980, years with high mean increases in short interest around the option introduction are often years with more negative abnormal return measures. The relationship between returns and ΔRSI will be investigated rigorously in a later section.

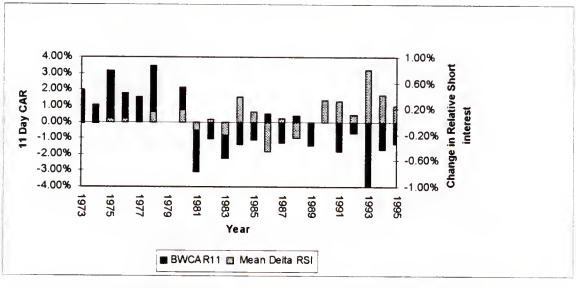

Figure 5-2. Annual Mean Abnormal Returns and Changes in Relative Short Interest

In order to discern the impact of lifting short-sale constraints, it will be desirable to utilize a more narrow one-month window, rather than the two-month window reported in Table 5-3. Unfortunately, this is not possible for all observations since short interest data are produced only on a monthly basis. Short interest data are available for transactions that settle by the 15th of each month. This implies, given 5 day settlements during the sample period, that the data include transactions executed before the 7th or 8th of each month. For option introductions that occur near the 7th of the month, we cannot synchronize the changes in short interest levels with the abnormal returns in a 6-day or 11-day event window. Approximately half of the observations can be utilized when a one month window is used.

Table 5-4 compares the subset of post-1980 option listings that occur on or after the 15th day of a month with the subset of listings occuring before the 15th. The listings occurring in the latter part of the month are sufficiently removed from the 7th so that short sales occurring on or after the option introduction cannot be included in the listing month data but must be reflected in the succeeding month data instead. This allows us to analyze the change in short interest for a one month window without fear that we have contaminated the ex-ante measure with transactions occurring after the option introduction. In contrast, option listings that occur in the first half of the month may produce short sales that will be captured in either the listing month's report or the subsequent report. Therefore, in order to be certain the ex-ante data is not contaminated, and that the ex-post data captures all of the option-related short interest, a larger two-month window must be examined. In order to better understand the ramifications of using a two-month window for part of the sample, Table 5-4 reports the short interest change occurring in both a one-month interval and in a two-month interval around the option introduction for the subset of listings occurring after the 15th. The F statistic p-value reported in each panel is the probability of variance equality between the one-month and two-month measurements.[1] This table reveals four interesting and important points that will be utilized in crafting subsequent empirical tests. These points are as follows:

1. Joint listings produce larger increases in short interest than call-only listings. (t=3.09)
2. Firms listed on NASDAQ have higher short interest increases than NYSE firms. (t=3.7)

[1] Missing short interest data points is responsible for the differing number of observations in the one-month vs. two-month samples.

3. The two month change in short interest is greater than the one month change. (t=1.97)

4. The variance of two-month changes is greater than the variance of one-month changes. (F statistic p-value<.0001)

While Tables 5-3 and 5-4 present the percentage increase in short interest relative to shares outstanding, Table 5-5 illustrates the very significant increase in short interest relative to ex-ante short interest levels. Post-listing mean short interest is nearly double the ex-ante level of short interest. Moreover, the median firm saw short interest rise by 16.5% for all post-1980 option introductions. NASD stocks saw larger median increases than exchange listed stocks.

Other data has been obtained from I/B/E/S, and the NYSE Transaction and Quote ("TAQ") files that include NASDAQ and AMEX firms as well as the NYSE firms implied by the name. The data collected from these sources are discussed in appropriate detail in the methodology discussion that follows.

Cross-sectional Tests on Abnormal Returns

We now turn to direct tests of the proposition that observed option-window returns are predicted by the firm's systematic risk and by the dispersion of investor expectations. The first test takes the following form:

Model 1: Explaining Abnormal Returns

$$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_\varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA \quad (1)$$

AR = abnormal returns as calculated using 6 methods discussed above

BWCAR11	Brown and Warner CARs over an 11 day window
BWCAR6	Brown and Warner CARs over an 6 day window
NOALPH11	Brown and Warner CARs with α=0 (11 days)
NOALPH6	Brown and Warner CARs with α=0 (6 days)
ABRET11	Stock return less Market Return over 11 days
ABRET6	Stock return less Market Return over 6 days

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model

SUMBETA the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW Standard deviation of the market model error in days t-100 to t-6

SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6

SDR1 Standard deviation of raw returns in days t-100 to t-6

SDR5 Standard deviation of five day raw returns in days t-100 to t-6

IBES The standard deviation of IBES long-term growth estimates

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)

Examining Model 1, we hypothesize that in addition to beta and the dispersion of expectations discussed previously in the theoretical model, two other factors might impact observed returns. Increased trading volume (ABVOL) may improve a stock's liquidity and several authors have observed an asymmetry in trading volume during rising markets versus declining markets.[2] ALPHA controls for the uncertainty surrounding the degree to which the estimation period alpha should be included in the abnormal return estimation. Each variable is discussed in the following paragraphs.

Beta

As noted in Chapter 4, a firm's beta should be positively correlated with pessimistic investors' desire to short a firm's stock. Intuition for this finding is straightforward if not obvious. Consider an investor who holds several stocks in his portfolio. To reduce the risk of these holdings, he might choose to underweight high beta stocks.[3] While we normally think of the investor eliminating high beta stocks in an extreme

[2]Harris and Raviv (1993)

[3]Obviously, he might choose to hold a zero beta security, T-bills. Shifting into T-bills is a special case of underweighting high-beta securities in that an increase in T-bills results in elimination of securities that are above the overall portfolio's mean beta.

example, in reality, the investor might choose to sell additional shares of the high beta stock since the transaction will further reduce his portfolio's beta if he is long in other stocks.

In the context of the Chapter 4 model, beta reflects the correlation between end-of-time prices on the stock and the market. In reality, the functional end of time differs across investors. For purposes of this study, two proxies for a representative end-of-time payoff structure are considered. BETA1 is the historical daily beta from the single factor market model between days t-100 to t-6. Due to nonsynchronous trading, BETA1 is downward biased for most firms since observed stock returns on smaller firms will lag the observed market movements. To control for this bias, SUMBETA is derived from the following estimation period model:

$$R_{it} = \alpha + \beta_1 R_{M(t)} + \beta_2 R_{M(t-1)} + \varepsilon$$

$$\text{SUMBETA} = \beta_1 + \beta_2$$

We expect the coefficient on either BETA proxy variable to be negative as predicted by the model.

Dispersion of Beliefs

Divergent opinion on a stock's future prospects may be related to investors' desire both to short the stock and to hedge long positions. Obviously, divergent opinion suggests a relatively large contingent of pessimists from whom the ranks of short sellers might be filled. Likewise, an optimist might rationally "hedge his bets" when confronted by a chorus of critics and carpers tracking a stock. Without regard to the impetus for

increased short sales, pessimists or guarded optimists, stocks with high belief dispersion should have the largest short-sale increases when options are introduced.

Five proxies for investor dispersion are analyzed. The first proxy for belief dispersion, SDR1, is the standard deviation of daily returns from day t-100 to day t-6. Numerous authors present theoretical models correlating belief dispersion with trading volume and trading volume with asset time-series volatility. Most recently, Shalen (1993) and Harris and Raviv (1993) develop models specifically examining the role of dispersion of investor opinion or beliefs, as opposed to the role of differentially informed investors, to investigate the role of dispersion on trading volume, volatility, and other trading characteristics. Shalen develops a noisy rational expectations model that shows that dispersion contributes to both a security's trading volume and the variance of price changes. Harris and Raviv produce a model in which investors update beliefs about returns using their own likelihood function of the relationship between news and the future prices. They demonstrate how investors who overestimate the true quality of the received signal will generate negative serial correlation along with higher trade volume. Jones, Kaul and Lipson (1994) find that contrary to "the apparent consensus even among academics that volume is related to volatility because it reflects the extent of disagreement about a security's value based on either differential information or differences of opinion," the number of trades, and not trade size, is the source of volatility. This suggests that volatility and trade frequency may be better proxies than volume for estimating dispersion of opinion or information. With specific reference to direct empirical support for volatility as a dispersion proxy variable, Peterson and Peterson (1982) demonstrate a positive and significant relationship between return volatility and the dispersion of I/B/E/S forecasts.

They also found that beta exhibited a positive correlation with I/B/E/S forecast dispersion, but this relationship was both less consistent and the correlations were of uniformly much smaller magnitude than the relationship between I/B/E/S dispersion and return volatility.

One potential bias with the proxy SDR1 arises from bid-ask bounce. In particular, NASDAQ firms had systematically and significantly higher spreads than NYSE listed firms prior to 1995. To reduce the effect of bid-ask bounce, SDR5 is offered as an alternative to SDR1. SDR5 is the standard deviation of weekly (5 day) returns from day t-250 to day t-6.

The third and fourth proxies for investor disagreement are the standard deviation of the error terms from the two alternative models used to estimate BETA1 and SUMBETA. These variables are referred to as SDEBW and SDESUMB, respectively.

The fifth proxy is the standard deviation of I/B/E/S long-term growth estimates. Use of this proxy assumes the dispersion of analysts' forecasts is positively correlated to the dispersion of investor forecasts. This seems reasonable.[4]

Abnormal Volume

An increase in volume around option introductions has been noted by numerous authors. Conrad suggested that increased volume and generally improved liquidity might account for the positive pre-1980 CARs that she reported. More recently, Sarin, Shastri and Shastri (1998) observe that option introductions coincide with improvement in several market liquidity measures including volume.

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[4]Market capitalization may also proxy for the dispersion of opinion on the future return potential of a firm. Small firms would be expected to generate relatively more short sales upon option introduction. This variable has been tested and evidence to date rejects capitalization and the log of capitalization as an additional explanatory factor in option listing window returns.

Based on these findings, we might expect that improved liquidity measures should be correlated not only with higher CARs but with increased short interest because improved liquidity reduces short sellers' risk of being caught in a squeeze. In the tests that follow, abnormal volume will proxy for improved general liquidity. Abnormal volume will be computed as the increase in average daily volume during the event window relative to the estimation period scaled by shares outstanding.

Alpha

As discussed in the description of the six abnormal return measures, the proper measurement of abnormal returns is uncertain. On one hand, we know that a selection bias exists in the data. Options tend to be introduced on high alpha stocks. Unless high alphas are expected to persist, inclusion of the alpha term in CAR computations will bias the abnormal return measure downward. On the other hand, excluding ALPHA from the abnormal return measure presumes that the true alpha in the event window is zero. In other words, we presume that estimation period alphas are wholly unimportant. Of course, we might guess that the true event window alpha is closer to zero than the estimation period alpha but not actually zero.

In order to avoid imposing a draconian assumption on the model, I include ALPHA as an explanatory variable. The sign on the ALPHA coefficients for BWCAR11 or BWCAR6 will be negative if the estimation period alphas are too large. Conversely, even if the estimation period alpha overstates the event window alpha, the zero-alpha assumption used to compute NOALPH11, NOALPH6, ABRET11 and ABRET6 will be baised if a non-zero alpha is appropriate. If the abnormal return measure should include a non-zero alpha, a positive coefficient on ALPHA will appear for dependent variables

NOALPH11, NOALPH6, ABRET11 and ABRET6. Notice that ALPHA is the estimated daily alpha while the left-hand-side variables are measured over six or eleven days. This calculation window disparity will be reflected in the magnitude of the coefficient on ALPHA.

Results

Table 5-6 depicts results from Model 1. Several interesting observations can be drawn from a perusal of Table 5-6. These results are summarized as follows:

- For BWCAR or NOALPH, using all dispersion proxies other than IBES, the regressions produce the anticipated negative coefficients on the BETA proxy and the σ_E proxy with one or both at statistically significant levels.[5] This result provides strong support for the model's contention that beta and dispersion of expectations are linked to overpricing that is lessened around the option introduction.
- For ABRET11, negative values for BETA and the dispersion proxies (excluding IBES) are also in evidence with one or both above 5% significance in four of the six specifications. Using ABRET6, all σ_E proxies are signed appropriately but never at significant levels. However, the BETA proxies show no support for the hypothesis when ABRET6 is the dependent variable. In fact, the wrong sign is in evidence for the BETA proxies in two of the six regressions. These results are less supportive of

[5]The single exception occurs in the 3rd regression of Panel B. Here, the t-stat on SDR5 is 1.61 and borders on standard significance.

the model predictions, but they are nevertheless supportive when viewed as a whole.

- IBES has no explanatory power in any regression. This result is somewhat surprising. The poor fit for the IBES proxy will be consistently repeated throughout this thesis. This poor performance could have two interpretations. First, the dispersion of IBES growth estimates may be a poor proxy for investors' dispersion of beliefs. On the other hand, the lack of significance may suggest that dispersion of expectations is unimportant in explaining the observed negative abnormal returns--a rejection of the hypothesis advanced in this thesis. As support for the first explanation, note that all four of the other dispersion proxies are significant in 23 of 24 specifications using BWCAR and NOALPH abnormal return measures, and the dispersion proxies are correctly signed for all 12 of the ABRET specifications with occasional significance.
- For the BWCAR and NOALPHA return measures, the independent variables explain a greater portion of the 11 day returns than the 6 day returns (i.e. adjusted R-squares are higher for the 11 day window)[6]. These results suggest that the independent variables better explain the longer measurement periods. One might interpret this as evidence that the abnormal returns begin to arrive before the actual option listing. Recall that Table 5-1 suggests the same interpretation.

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[6]The ABRET measures show no clear difference in adjusted R-squares between the two return measures.

- Increased volume, ABVOL, is positively correlated with returns for all six dependent variable measures, but the relationship lacks statistical significance for the ABRET measures. Recall that the expected sign on this variable is positive, and this ins what we actually observe..
- ALPHA is significantly negative for the BWCAR measures and significantly positive for NOALPH and ABRET suggesting the "true" specification should have some portion of the estimated alpha deducted in the return benchmark. This result is not surprising, and it reinforces the propriety of explicitly controlling for the partial inclusion of alpha in the computation of the abnormal return metrics by including ALPHA as a regressor.

Robustness Checks

We have observed that both BETA and σ_E proxies (other than IBES) produce the expected negative values for the BWCAR and NOALPH measures. In addition, BETA and σ_E variables have negative coefficients for ABRET11 and ABRET6, but the level of statistical significance declines, particularly for ABRET6. A possible problem with the Panel F regressions may be that the correlation between BETA proxies and σ_E proxies inflates the standard error estimates when both variables are included together in the regression.[7] To eliminate this potential problem, I offer the following alternative specifications:

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[7] The variance-inflation factor (VIF) derived from regressing SDESUMB on the other right-hand side variables is 1.51. Ideally, the VIF would be zero, but a VIF of this magnitude is generally not considered indicative of severe multicollinearity. See Maddala's *Introduction to Econometrics*, Chapter 7.3.

Model 2: Purging BETA on σ_E

$$AR = \alpha_0 + \alpha_1 \varepsilon + \alpha_2\sigma_E + \alpha_3 ABVOL + \alpha_4 ALPHA + \gamma \quad (2)$$

$$BETA = \beta_0 + \beta_1\sigma_E + \varepsilon \quad (3)$$

Model 3: Purging σ_E on BETA

$$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA + \gamma \quad (4)$$

$$\sigma_E = \beta_0 + \beta_1 BETA + \varepsilon \quad (5)$$

Equation (3) orthogonalizes BETA to σ_E. By using the error term in Equation (2) in place of BETA, we can isolate the effect of σ_E on the dependent variable while examining whether the BETA variable provides any additional explanatory power. Obviously, Model 3 is the mirror image of Model 2 and will allow us to examine the explanatory power of BETA with the marginal contribution of σ_E.

In considering the reported ε coefficient values below, the reader must understand that ε is not a true substitute for the raw value that ε replaces in these two models. Instead, ε should be thought of as the portion of the Equation 3 or Equation 5 dependent variable that can not be proxied by the right hand side variable. In this sense, ε is the extra information carried by the variable rather than all of the information contained in the raw value.

The results of these regressions are presented in Panels A-F of Table 5-7. The results displayed in this table are compelling. In each of the 11-day-window regressions the raw σ_E or raw BETA (as opposed to the orthogonalized ε value) is significantly negative, usually at the 1% level. Moreover, for BWCAR11 and NOALPHA11, the orthogonalized ε value coefficient (α_1 in Model 2, α_2 in Model 3) is also significantly negative. The Panel E regressions, which explain ABRET11, support this finding in that 3 of the 6 orthogonalized ε coefficients are also negative at levels of high statistical significance.

BWCAR6 and NOALPH6 (Panels B and D) produce results that are highly supportive of the finding that the coefficient on the raw σ_E or BETA is negative at high significance levels, but they provide weaker support for negative ε coefficients. Only ABRET6 in Panel F can be said to provide only weak evidence of the expected relationship although it reports all of the raw σ_E or BETA coefficients and most of the ε coefficients with the expected sign.

Taken as a whole, the results of Tables 6 and 7 suggest that BETA and σ_E are predictors of returns around the option introduction date, and that these variables perform as though short-sale constraint relaxation is a factor that contributes to the abnormal returns. These results are consistent with the theoretical model produced in Chapter 4, and they provide encouragement to look for a similar relationship between changes in short interest and the σ_E or BETA proxies.

Trading Volume Anomaly

Before departing from this analysis of the correlation of returns to BETA and the dispersion proxies, an interesting anomaly in the data is worthy of discussion. In order to highlight the salient issue, consider the following simplifications on Model 1:

Model 4: Explaining Abnormal Returns with dispersion proxies
$$AR = \alpha_0 + \alpha_1\sigma_E + \alpha_2 ABVOL + \alpha_3 ALPHA \quad (6)$$

Model 5: Explaining Abnormal Returns with BETA proxies
$$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 ABVOL + \alpha_3 ALPHA \quad (7)$$

Table 5-8 provides the results of these regressions for the abnormal return measure ABRET11 using SDESUMB as the σ_E dispersion proxy and SUMBETA as the BETA proxy. The choice of the dependent variable and right-hand-side proxy variables is relatively arbitrary since very similar results are produced for other combinations that do

not include IBES as a dispersion proxy. Notice that three cases are presented for both models. In the first column for each model, the sample size is 1426 and is composed of the identical set of observations presented in Tables 5-6 and 5-7. The second and third columns in each model bifurcate the sample into "low volume" and "high volume" subsets. The points of bifurcation in each model are selected because they represent the points at which the SDESUMB and SUMBETA coefficients cease to be significant for the low-volume firms while the high-volume subsets retain statistical significance despite the smaller sample size. The Model 4 low-volume subset contains the 1263 observations with the lowest average daily trading volume[8] in the 95 trading days prior to the date t-5, the beginning of the event window. The high-volume subset contains the 163 firms with the highest average daily volume.

For the full sample of 1426 observations in Model 4, SDESUMB carries a statistically significant negative value of –58.0416, but the bifurcation reveals that the size and significance of the coefficient is driven by the subset of high-volume stocks. Among this subset, the value of SDESUMB is –138.057 while the coefficient for the low-volume subset is –42.6348. In fact, as successive high volume firms are excluded from the low-volume subset, the coefficient on SDESUMB continues to drift upward toward zero. A similar but less pronounced behavior occurs for SUMBETA in Model 5. Note that the 283 highest volume firms must be excluded from the low-volume set before SUMBETA ceases to evidence a statistically significant negative value. In order to present a more comprehensive view of the effect of low-volume versus high-volume stocks, turn your attention to Figures 5-3 and 5-4.

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[8] NASDAQ volume is halved to correct for "double counting" on NASDAQ.

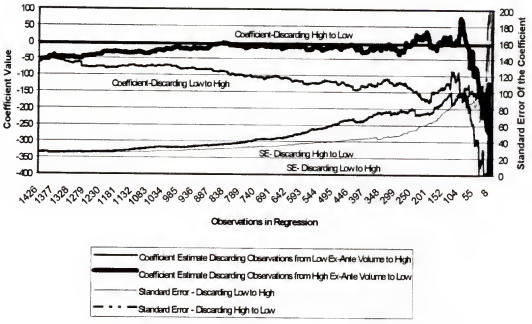

Figure 5-3. SDESUMB Coefficient Estimates for Iteratively Smaller Sample Sizes (Model 4)

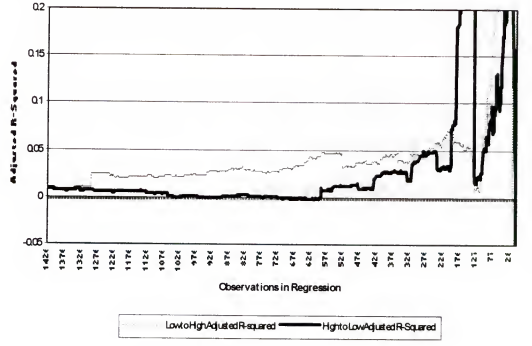

Figure 5-4. Adjusted R-Squares for Iteratively Smaller Sample Sizes (Model 4)

Figure 5-3 presents Model 4's coefficient estimates on SDESUMB along with the standard error of each estimate. The line on the chart described as "Coefficient--Discarding High to Low" depicts the coefficient estimates that are produced as successively lower volume stocks are excluded from the data set. For example, when the number of observations is 1326, the 100 stocks with the highest pre-listing trading volume have been eliminated from the regression. The line titled "Coefficient –Discarding Low to High" represents the coefficient value when the lowest volume firm is discarded first and successively larger firms are later expelled.

Notice that the line "Coefficient--Discarding Low to High" is below the "Coefficient--Discarding High to Low" line. This means that the effect of excluding high volume firms is to drive the coefficient estimate downward while exclusion of low volume firms does the opposite. We must be careful not to interpret this as high-volume firms falling in value more than low-volume firms. Rather, the relationship between SDESUMB and ABRET11 is more pronounced among high-volume firms.

The standard errors for the two coefficient lines also are shown on Figure 5-3 (see right axis for scale). Generally, as firms are excluded from the regression, the standard errors rise.[9] However, the standard errors rise slightly more rapidly as high-volume firms are excluded. This suggests that the relationship between SDESUMB and ABRET11 is not only stronger for the high-volume firms, but the coefficient estimates are more precise as well. This assertion is further demonstrated in Figure 5-4, which provides the adjusted R-square for each regression. Observe that for larger samples (i.e., the left-hand portion of

[9]Obviously, reducing the sample size will increase standard errors, all else equal.

the graph) the adjusted R-square is higher when low-volume stocks are excluded than when high-volume stocks are excluded.

Figures 5-5 and 5-6 present similar though less stunning results for Model 5, and the results depicted in Figures 5-3, 5-4, 5-5, and 5-6 are robust to the abnormal return proxy chosen. The clear implication of these findings is that the results that we earlier observed for the full sample in Tables 5-6 and 5-7 are driven largely by high-volume firms. When these firms are systematically expunged from the data, the results deteriorate.

One possible explanation for this phenomenon could be that the problems with computing abnormal returns as well as dispersion and beta proxies are more severe for lightly traded firms than for more active stocks. However, when ex-ante relative short interest (EARSI) is substituted for the abnormal return measure, the dichotomy between high-volume and low-volume firms remain. The regressions that consider EARSI are presented later in this chapter. However, the fact that the pattern is apparent when the left-hand side variable is changed suggests that measurement error in the abnormal return measures is not responsible for the pattern shown in Figures 5-3, 5-4, 5-5, and 5-6.

A more likely explanation is that an error in variables problem is present since measurement error in a proxy variable attenuates the coefficient value on that proxy toward zero.[10] This problem could arise from estimation error in the dispersion and BETA proxies. Assuming that beta and dispersion can be more accurately estimated for high volume firms, the exclusion of high-volume firms will aggravate the error in variables problem as more noisy low-volume observations comprise the remaining sample. If the low-volume firms have beta and dispersion proxies that are measured with larger error,

[10]See Green's Econometric Analysis, Second Edition, page 294.

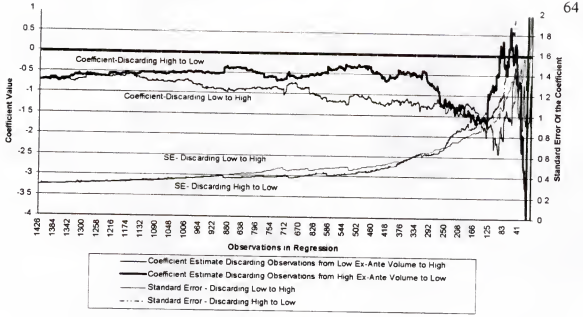

Figure 5-5. SUMBETA Coefficient Estimates for Iteratively Smaller Sample Sizes (Model 5)

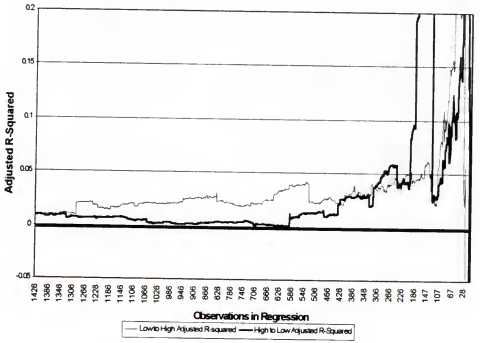

Figure 5-6. Adjusted R-Squares for Iteratively Smaller Sample Sizes (Model 5)

exclusion of the less noisy large volume firms attenuates the proxy coefficient toward zero.

In contrast, excluding the more noisy small-volume observations eliminates attenuation in the remaining high-volume sample--a result consistent with Figures 5-3 and 5-5. In any event, if an error in variable problem is present, we can take some comfort in the fact that the full sample produces significant coefficient values despite the possibility that these values are biased toward zero.[11]

Cross-sectional Tests on Ex-ante Relative Short Interest

Having examined the effect of option introductions on a wide range of alternative abnormal returns, we next turn our attention to the effects of option listing on short interest levels. The model produced in Chapter 4 predicts that firms with high beta and dispersion of expectations will have higher levels of short interest when no short-sale constraint is in place. To this point, I have argued that option introductions act to eliminate a short-sale constraint, and we should expect that short interest will rise upon option listing. Moreover, the short interest of stocks with high betas and high expectations dispersion should rise more than that of stocks with low betas and low dispersions.

However, before turning to the effect of option listing on changes in short interest levels, let us first consider the obvious fact that prior to each option introduction, the subject stock almost always evidences short interest. The obvious implication of this observation is that prior to the option listing, the degree to which short sales are restricted

[11]Unfortunately, errors in the proxy variable will also bias the other coefficients in unknown ways. This may place the results of these coefficient estimates in doubt. Fortunately, the estimates of ABVOL and ALPHA are not the principal focus of our tests.

is less than absolute. If the restriction were absolute, we would see no pre-option short selling at all.

Since short selling exists prior to the option introduction, we can gain some important insights on the relationship between short selling and beta or short selling and the dispersion of expectations. This relationship is obviously of great importance since I theorize that beta and dispersion of expectations are important determinants of short interest levels when short sales are allowed.

Examining the relationship between pre-option ("ex-ante") short interest and the determinants of short selling offers some advantages over searching for the relationship between these determinants and ΔRSI. First, the ex-ante relative short interest ("EARSI") measures the level of short interest while ΔRSI measures the change in the level of short interest. Given the time series volatility that a stock's short interest displays, efforts to measure the change induced by a change in the constraint level may be frustrated by the noisiness of ΔRSI. As I have discussed previously, short interest fluctuates during the listing month for many reasons–not solely due to the option listing itself.

Using ex-ante data allows us to interpret the pre-option listing level of short interest as a "change" relative to an absolute prohibition on short selling. In this sense, we can examine the impact of relaxing the short-sale prohibition in a generic sense. If beta and dispersion of expectations do not show evidence that they influence short interest in this more general framework, we should suspect that they may fail to show an impact in the less generic option listing tests.

A second advantage of using EARSI is that we face no uncertainty over an appropriate measurement window for computing EARSI. As we have acknowledged previously,

ΔRSI must be measured over a one-month or two-month period with the necessity/appropriateness of a two-month measurement period dictated by our inability to measure a "clean" one-month change. Recall that the frequent problem in measuring a one-month change stems from the fact that the option listing date often falls too near the short interest measurement date for the month. In contrast, without regard to the day of the month on which the option was introduced, every stock for which short interest has been measured can be included in the tests using EARSI as the dependent variable. Obviously, this characteristic is attractive as contrasted with the need to control for differences in event window lengths as will be required with ΔRSI.

The Initial Tests

Turning to the tests to be conducted on EARSI, let us examine Model 6 as follows:

Model 6: Explaining Ex-Ante Relative Short Interest

$$EARSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \tau \qquad (8)$$

EARSI=Short Interest prior to the option introduction divided by outstanding shares.
BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

EARSI is defined as the short interest level prior to the option introduction. If the option is introduced prior to the 23rd day of the month, the short interest level reported for the

previous month is used. If the listing occurs on or after the 23rd, the short interest reported for the month of listing is used. Thus, the short interest measurement date precedes the listing date by at least 15 calendar days, a period that should suffice to exclude any effects of the option introduction.

The proxy variables that are included in Model 6, by now, are known to the reader. We expect the coefficient signs on the BETA and dispersion proxies to be positive since the Chapter 4 model predicts a higher level of short interest for high beta and high dispersion of expectations firms. Unlike the regression specifications used to explain abnormal returns, I have not included ABVOL and ALPHA in this regression specification since there is no theoretical justification for their inclusion.[12]

Table 5-9 presents the results of these regressions. As we have predicted, the BETA and dispersion of expectations variable show a strong relationship to EARSI. In most cases, the coefficient values on these variables are positive and significant. The two exceptions to this general assertion involve SUMBETA and IBES proxies. IBES once again fails to produce a statistically significant result although the positive values on these coefficients are approaching significance with the predicted arithmetic sign. More troubling is the fact that SUMBETA does not produce high statistical significance when paired with dispersion proxies other than IBES. However, once again, the "correct" positive sign is attached to these values, and modest improvement in the significance levels would produce statistically significant results. ($t = 1.642$ in one instance.)

[12]However, the inclusion of these variables does not change the salient results.

Robustness Checks

As I have previously done in Models 2 and 3 where I sought to explain abnormal returns in the listing window, I now consider the possibility that the correlation between BETA and σ_E inflates the standard error estimates when both variables are included together in the regression. Consider the following alternative specifications:

Model 7: Purging BETA on σ_E

$$EARSI = \alpha_0 + \alpha_1 \varepsilon + \alpha_2 \sigma_E + \gamma \quad (9)$$

$$BETA = \beta_0 + \beta_1 \sigma_E + \varepsilon \quad (10)$$

Model 8: Purging σ_E on BETA

$$EARSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \varepsilon + \gamma \quad (11)$$

$$\sigma_E = \beta_0 + \beta_1 BETA + \varepsilon \quad (12)$$

The results of these regressions are presented in Table 5-10. As we would expect, in each of the regressions the raw σ_E or BETA (as opposed the orthogonalized ε value) is significantly positive at the 1% level. Notice that this is also true for SUMBETA, which failed to attain significance when paired with several non-orthogonalized dispersion proxies in Table 5-9. Moreover, with the exception of SUMBETA, the orthogonalized ε value coefficient (α_1 in Model 7, α_2 in Model 8) is also significantly positive. Even for SUMBETA, the value of this coefficient is positive and comes very close to attaining significance. ($t = 1.643$).

Taken as a whole, the results of Tables 5-9 and 5-10 suggest that BETA and σ_E are predictors of EARSI, and these variables perform as though short interest levels are partially determined by these factors consistent with the theoretical model produced in Chapter 4. Moreover, these empirical results suggest that if option introductions further relax short-sale constraints, we can expect similar results if we replace EARSI with ΔRSI. We find these results in the next section.

A Note on the Residual Values--Tau

Before turning to a discussion of ΔRSI, it is worthwhile to discuss a possible interpretation of τ in Model 6. Recall from Figure 5-1 that the equilibrium level of short interest is at the intersection of the supply and demand curves for each stock. We have thus far produced evidence consistent with using BETA and σ_ε as proxies that describe the slope of the demand curve in Figure 5-1. Since Model 6 defines a relationship between EARSI and these demand factors, one might reasonably interpret τ as a measure of the supply curve for a particular stock. Since Model 6 defines a relationship between EARSI and these demand factors, one might reasonably interpret τ as a measure of the constraints on short selling prior to the option introduction.

For example, consider Figure 5-7 where EARSI is a function of the firm's beta and $\overline{EARSI}$ might be fit to the data by an OLS regression. Consistent with prior discussions, the ex-ante relative short interest rises as beta rises, signifying that the supply of shares will increase with beta. In other words, the desire among pessimists to sell short increases as beta increases. However, most observations will actually lie above or below the anticipated (fitted) value. This divergence from the expected value is captured by τ from Model 6. Thus, τ can be viewed as measuring the degree to which a security is ex-ante short-sale constrained relative to the other observations in the sample.[13] The point labeled "A" denotes a relatively unconstrained stock because more short interest is in evidence than the fitting regression predicts. In contrast, point "B" represents a relatively unconstrained security.

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[13] Obviously, the regression tells us nothing about the degree of constraint relative to out-of-sample securities.

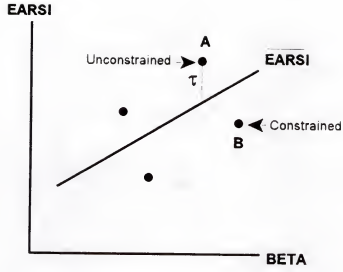

Figure 5-7. Ex-Ante Relative Short Interest as a function of Beta

Using this interpretation, companies that have high residual values may be said to be relatively unconstrained in that they exhibit more short interest than the average firm possessing the same demand characteristics. Likewise, firms that are relatively constrained should exhibit negative residual values. I will return to τ as a metric in Chapter 6 when a measure of firms' short-sale constrainedness becomes useful.

Cross-sectional Tests on ΔRSI

Having tested and confirmed a relationship between ex-ante short interest and the proxy variables for demand factors, we now turn our attention to the issue of whether option introductions' increased short interest can be explained by these same variables. In other words, is the option-related change in short interest correlated with BETA and σ_E? Along with Table 5-6's regression results using abnormal returns as the dependent variable, the following specification represents the most important empirical test in the

paper since it produces a direct test of the theoretical model in Chapter 4. Consider the following specification:

Model 9: Explaining Changes in Relative Short Interest

$$\Delta RSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 ABVOL + \alpha_4 ALPHA + \alpha_5 ONEMONTH \quad (13)$$

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

BETA = the Beta in the 95 trading days preceding the event window computed as either

- BETA1 — a single market factor model
- SUMBETA — the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

- SDEBW — Standard deviation of the market model error in days t-100 to t-6
- SDESUMB — Standard deviation of the summed beta model error in days t-100 to t-6
- SDR1 — Standard deviation of raw returns in days t-100 to t-6
- SDR5 — Standard deviation of five day raw returns in days t-100 to t-6
- IBES — The standard deviation of IBES long-term growth estimates

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)

ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

In addition to the familiar variables, the new variable ONEMONTH is added to the right-hand side of this equation. The necessity of including this variable results from two econometric complexities both of which stem from the coarseness of short interest data. Recall that short interest data is reported on a monthly basis only. Obviously, these monthly reports will measure changes in the desired 11-day or 6-day interval around the option listing with significant error. The reader will recall that the longer of the two abnormal return event windows examined is only eleven days, but the short interest change we must use is for a full month, at best. Unfortunately, for our purposes, even monthly short interest change observations are not useful for many option introductions

because the listing date falls too near the short interest measurement date. Consider the following time line:

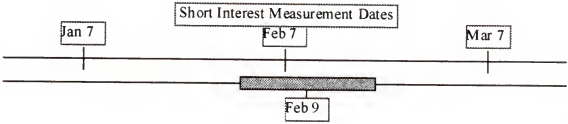

Figure 5-8. Comparison of an Event Window with Short Interest Observation Dates

Suppose an option is introduced on February 9 and short sales are measured for transactions on or before the 7th of the month. In this case, the February 7th short interest observation lies inside the eleven-day listing event window shown as the shaded area. In order to observe the full effect of possible changes in short sales during the event window, we must look at the change that occurs from January to March, a two month change. In order to insure that the event window returns always occur between two short interest measurement dates, options introduced on the 1st or from the 15th to the 31st of a month will utilize a 1 month change in short interest. Options introduced between the 2nd and 13th of the month will use two month ΔRSI windows since the short interest collection date (approximately the 7th of each month) falls within the event window.[14]

[14]Short Interest information is collected by the exchanges and by the NASD for transactions occurring on or before approximately the 7th of each month. The data is published on approximately the 15th of the month.

Recalling the results presented in Table 5-4, the variable ONEMONTH controls for the greater short interest increases in two-month short interest measurement windows than one month windows. This variable should carry a negative coefficient consistent with observations in Table 5-4.

In addition to controlling for mean differences in the two subsamples, a difference in the variance of ΔRSI for the one-month versus two-month short interest measurement windows is demonstrated by the F statistics shown in each panel of Table 5-4. The inequality of variance in ΔRSI produces groupwise heteroscedasticity resolved by weighting the least squares regression by the appropriate group residual variance.[15]

Turning to the expected results of this specification, recall that I have argued option listings allow synthetic short positions to be transformed into actual short sales via market-maker hedging. Therefore, as with the regressions using EARSI as the dependent variable, I expect the coefficients on BETA and σ_E to be positive. In other words, these proxy variables denote increased demand to sell short as they rise, and this demand will be more fully acted upon after each option's introduction.

Our ex-ante expectation concerning the value on ABVOL is that it may carry a positive sign since a large increase in volume will presumably be accompanied by more short sales. One reason this might occur is that increased liquidity could act to reduce the costs of short selling. However, even without a change in short-sale constraint levels, greater volume will reflect both long-initiated and short-initiated transactions.

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[15]Greene's *Econometric Analysis, Second Edition* provides a clear and concise discussion of this method of controlling for groupwise heteroscedasticity. See Chapter 13, Nonspherical Disturbances.

The sign on ALPHA is expected to be zero, but I have included ALPHA as an explanatory factor since the abnormal returns are affected by the variable. Presumably the relationship between ALPHA and these abnormal return proxies results from imperfections in the various abnormal return measures. However, if ALPHA possesses a non-negative coefficient in the following ΔRSI regressions, we will need to reconsider the roll ALPHA played in the earlier abnormal return regressions.

Turning to the results in Table 5-11, we find that BETA and σ_E possess positive coefficient signs as we projected. Except for IBES, the coefficients on all dispersion proxies are statistically significant. As for IBES, we have come to expect and accept the failure of this proxy. The positive BETA coefficients are statistically significant in five of eight instances.

As for the other two variables, ALPHA cannot be said to differ from zero (it fails to attain significance in seven of eight cases), and ONEMONTH possesses the expected negative sign, a result that echoes the findings presented in Table 5-4.

Robustness Checks

Repeating the purging regressions performed with EARSI as the dependent variable, I consider the possibility that the correlation between BETA and σ_E proxies biases both values toward zero when both are included together in the regression. The new specifications follow.

Model 10: Purging BETA on σ_E

$$\Delta RSI = \alpha_0 + \alpha_1 \varepsilon + \alpha_2 \sigma_E + \alpha_3 \text{ ABVOL} + \alpha_4 \text{ALPHA} + \alpha_5 \text{ONEMONTH} + \gamma \quad (14)$$

$$\text{BETA} = \beta_0 + \beta_1 \sigma_E + \varepsilon \quad (15)$$

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

Model 11: Purging σ_E on BETA

$$\Delta RSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA + \alpha_5 ONEMONTH + \gamma \quad (16)$$

$$\sigma_E = \beta_0 + \beta_1 BETA + \varepsilon \quad (17)$$

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

The results of these regressions are presented in Table 5-12. Each of the regressions of raw σ_E or BETA (as opposed the orthogonalized ε value) is significantly positive at high significance levels. Also, in seven of eight cases, the orthogonalized ε coefficient (α_1 in Model 10, α_2 in Model 11) is also significantly positive. In the instance where significance is not attained, the sign is positive nevertheless.

Once again, the value of ONEMONTH's coefficient is consistently negative at high levels of probability, and ALPHA produces only weak evidence of a non-zero coefficient. As for ABVOL, the coefficient value is convincingly positive as we expected.

Taken as a whole, the results presented in Tables 5-11 and 5-12 along with other robustness checks suggest that short interest is strongly correlated with beta and the dispersion of investor expectations as proxied in this paper. This is a major finding as it supports the predictions of the theoretical sections of this thesis.

ΔRSI Regressed on Abnormal Returns

Having demonstrated a relationship between ΔRSI and the demand factors of interest, I now turn to the final prediction of the theoretical model presented in Chapter 4. To test whether the abnormal returns and ΔRSI are negatively correlated, I conduct the following test:

Model 12: Examining Changes in Relative Short Interest and Abnormal Returns

$$\Delta RSI = \alpha_0 + \alpha_1 AR + \alpha_2 ABVOL + \alpha_3 ALPHA + \alpha_4 ONEMONTH \quad (18)$$

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

AR = abnormal returns as calculated using 6 methods discussed above

BWCAR11	Brown and Warner CARs over an 11 day window
BWCAR6	Brown and Warner CARs over an 6 day window
NOALPH11	Brown and Warner CARs with α=0 (11 days)
NOALPH6	Brown and Warner CARs with α=0 (6 days)
ABRET11	Stock return less Market Return over 11 days
ABRET6	Stock return less Market Return over 6 days

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

By now, the reader is familiar with each of these variables. We anticipate that the abnormal return coefficients will be negative (i.e. short interest rises as returns fall) and that ABVOL will possess a positive coefficient while ONEMONTH produces a negatively signed value. As we have done previously, the regressions are weighted to correct for the groupwise heteroskedasticity that results from combining heterogeneous ΔRSI measurement intervals. The results are presented in Table 5-13 with all of the expected results in evidence.

Notice that ABVOL and ONEMONTH produce the same qualitative results we observed in Table 5-12 and that the expected negative sign is attached to each of the abnormal return proxies. Moreover, each of these proxy coefficient values is statistically significant at the 5% level with the exception of NOALPH6 that evidences a t statistic of 1.54.

All of these results are consistent with a correlation between ΔRSI and the listing window abnormal returns. However, once again, we cannot attach any inference of causation due to the fact that neither ΔRSI nor AR is, in truth, an independent variable.

Summary

In summary, the empirical tests conducted in this chapter serve to validate each of the predictions of the theoretical model in Chapter 4. Specifically, the firm's beta and the dispersion of investor expectation proxies are positively correlated with ΔRSI and negatively correlated with abnormal return measures. The relationship observed between these factors and ΔRSI is reinforced by near-identical findings when EARSI replaces ΔRSI as the left-hand-side variable. Moreover, the hypothesized negative correlation between ΔRSI and abnormal returns is also empirically supported.

Table 5-1
Descriptive Statistics–Abnormal Returns by Year

PANEL A

All stocks, call-only and joint listings, by year

Year	LISTINGS	BWCAR11	T-Stat	BWCAR6	T-Stat
1973	27	1.96%	1.30	2.30%	2.56
1974	6	1.04%	1.35	-0.80%	0.39
1975	87	3.16%	3.35	2.14%	2.92
1976	57	1.78%	-0.07	1.38%	0.17
1977	18	1.52%	-0.29	1.34%	0.44
1978	5	3.46%	1.06	1.79%	2.32
1979	0				
1980	41	2.13%	0.16	1.22%	0.86
1981	9	-3.08%	-1.47	-0.27%	-0.34
1982	76	-1.03%	-1.77	-0.38%	-0.40
1983	26	-2.26%	-1.81	0.30%	-0.41
1984	11	-1.43%	-3.72	-2.41%	-3.60
1985	51	-1.09%	-0.57	0.86%	0.76
1986	34	0.52%	-0.49	0.86%	0.18
1987	100	-1.27%	-2.59	-0.56%	-2.28
1988	93	0.37%	-0.47	0.74%	0.42
1989	83	-1.50%	-1.41	-1.51%	-2.88
1990	112	0.31%	1.70	-0.52%	0.44
1991	136	-1.85%	-3.41	-0.33%	-1.90
1992	121	-0.67%	-0.09	-0.46%	0.21
1993	192	-3.96%	-4.85	-2.78%	-4.05
1994	181	-1.72%	-2.17	-0.85%	-1.35
1995	202	-1.38%	-0.50	-0.58%	-0.74
Pre-1981	241	2.35%	2.26	1.68%	3.16
Post-1980	1427	-1.46%	-5.17	-0.74%	-3.74

t statistic for equality of means (Pre-1981vs Post-1980)

t=4.17 t=4.48

Table 5-1--Continued

PANEL B

All stocks, call-only and joint listings, by year

Year	LISTINGS	NOALPH11	T-Stat	NOALPH6	T-Stat
1973	27	2.06%	1.72	2.30%	2.61
1974	6	2.09%	1.98	-0.80%	0.72
1975	87	3.21%	4.28	2.14%	3.78
1976	57	2.15%	0.87	1.38%	1.11
1977	18	2.94%	0.99	1.34%	2.37
1978	5	4.67%	1.01	1.79%	2.34
1979	0				
1980	41	2.26%	0.48	1.22%	0.64
1981	9	-2.22%	-0.91	-0.27%	0.01
1982	76	-0.87%	-0.26	-0.38%	0.85
1983	26	-1.56%	-1.70	0.30%	0.29
1984	11	-0.46%	-0.03	-2.41%	-0.94
1985	51	-1.36%	-0.18	0.86%	1.23
1986	34	0.98%	0.16	0.86%	0.56
1987	100	-0.70%	-2.70	-0.56%	-2.41
1988	93	1.07%	0.57	0.74%	1.75
1989	83	-1.07%	-0.70	-1.51%	-2.07
1990	112	0.30%	2.40	-0.52%	0.62
1991	136	0.46%	-0.13	-0.33%	0.80
1992	121	0.94%	2.06	-0.46%	1.60
1993	192	-1.46%	-0.90	-2.78%	-1.44
1994	181	-0.26%	0.60	-0.85%	0.75
1995	202	0.27%	1.52	-0.58%	1.02
Pre-1981	241	2.65%	4.17	1.84%	4.82
Post-1980	1427	-0.20%	0.46	-0.07%	0.83

t statistic for equality of means (Pre-1981vs Post-1980)

t=3.63 t=4.19

Table 5-1--Continued

PANEL C

All stocks, call-only and joint listings, by year

Year	LISTINGS	ABRET11	T-Stat	ABRET6	T-Stat
1973	27	1.34%	1.96	2.68%	3.11
1974	6	2.19%	1.07	-0.29%	-0.70
1975	87	3.65%	3.64	2.47%	4.09
1976	57	2.48%	1.29	1.68%	1.07
1977	18	2.44%	1.06	2.00%	0.49
1978	5	2.83%	0.59	1.19%	0.75
1979	0				
1980	41	3.40%	2.12	1.78%	1.65
1981	9	-3.45%	-0.52	-1.66%	0.14
1982	76	-1.08%	-0.06	-0.24%	0.59
1983	26	-1.06%	-0.66	1.40%	1.28
1984	11	-0.01%	-0.73	-1.64%	-2.45
1985	51	-0.52%	0.86	1.13%	2.13
1986	34	0.58%	0.94	1.28%	2.15
1987	100	-0.38%	-0.59	-0.01%	-0.20
1988	93	1.05%	1.29	1.07%	1.72
1989	83	-1.22%	-0.39	-1.20%	-1.64
1990	112	0.37%	0.47	-0.59%	-1.22
1991	136	0.75%	-0.12	1.15%	0.32
1992	121	1.01%	2.23	0.63%	1.08
1993	192	-1.33%	-2.25	-1.31%	-2.59
1994	181	-0.19%	1.00	-0.01%	0.50
1995	202	0.76%	0.40	0.82%	0.71
Pre-1981	241	2.93%	4.61	2.06%	4.64
Post-1980	1427	-0.04%	0.64	0.12%	0.47

t statistic for equality of means (Pre-1981vs Post-1980)

t=3.63 t=3.81

Cumulative Abnormal Returns are computed over both a six day and an eleven day six day window Six day CARs are aggregated from the option listing date (t=0) to day t+5. Eleven day CARs are aggregated from dates t-5 to t+5. The reported T-statistics are computed after adjusting the CARs for heteroscedasticity using the variance of each CAR estimate as described in Houston and Ryngaert (1994).

Table 5-2
Descriptive Statistics–Abnormal Returns by Various Characteristics

All stocks, call-only and joint listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1973-1980	241	0.02	2.26	0.02	3.16
1981-1995	1427	-0.01	-5.17	-0.01	-3.74

All stocks, call-only listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1973-1980	237	0.02	2.03	0.02	3.09
1981-1995	337	-0.01	-4.18	0.00	-1.81

All stocks, joint listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1973-1980	4	0.06	3.30	0.02	0.60
1981-1995	1090	-0.02	-3.48	-0.01	-3.28

NYSE stocks, call-only and joint listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1973-1980	237	0.02	2.26	0.02	3.17
1981-1995	718	-0.01	-2.57	-0.01	-2.62

AMEX stocks, call-only and joint listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1973-1980	4	0.02	-0.06	0.04	0.19
1981-1995	58	-0.03	-2.78	-0.01	-2.75

NASD stocks, call-only and joint listings

Years	Number of Listings	BWCAR11	T-Stat	BWCAR6	T-Stat
1981-1995	651	-0.02	-4.77	-0.01	-1.97

Cumulative Abnormal Returns are comuted over both a six day and an eleven day six day window. Six day CARs are aggregated from the option listing date(t=0) to day t+5. Eleven day CARs are aggregated from dates t-5 to t+5. The reported T-statistics are computed after adjusting the CARs for heteroscedasticity using the variance of each CAR estimate as described in Houston and Ryngaert (1994).

Table 5-3
Descriptive Statistics--Change in Relative Short Interest

All stocks, call-only and joint listings, by year

Years	List-ings	Delta RSI	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973	18	-0.02%	-0.56	0.14%	-0.44%	-0.05%	0.00%	0.02%	0.30%
1974	6	-0.02%	-0.62	0.10%	-0.21%	-0.06%	0.00%	0.03%	0.07%
1975	80	0.05%	1.35	0.34%	-0.31%	-0.01%	0.00%	0.04%	2.82%
1976	47	0.05%	2.07	0.15%	-0.28%	-0.01%	0.02%	0.11%	0.52%
1977	13	0.01%	0.11	0.28%	-0.49%	-0.07%	0.00%	0.04%	0.72%
1978	5	0.17%	1.13	0.33%	-0.05%	-0.03%	0.06%	0.41%	0.74%
1979	0								
1980	40	0.18%	1.81	0.63%	-1.13%	-0.01%	0.04%	0.18%	3.41%
1981	9	-0.12%	-0.73	0.51%	-1.08%	-0.49%	-0.07%	0.30%	0.49%
1982	70	0.03%	0.67	0.39%	-1.79%	-0.03%	0.02%	0.11%	1.10%
1983	22	-0.21%	-0.77	1.25%	-5.61%	-0.09%	-0.04%	0.07%	1.33%
1984	10	0.38%	1.75	0.68%	-0.21%	-0.01%	0.07%	0.78%	1.97%
1985	30	0.16%	1.70	0.52%	-0.79%	-0.01%	0.08%	0.28%	2.11%
1986	18	-0.46%	-0.84	2.30%	-9.44%	-0.18%	0.03%	0.17%	1.61%
1987	95	0.06%	1.03	0.54%	-1.85%	-0.06%	0.04%	0.19%	2.00%
1988	76	-0.25%	-0.72	3.06%	-25.90%	-0.07%	0.08%	0.24%	2.67%
1989	70	-0.02%	-0.11	1.87%	-10.15%	-0.05%	0.02%	0.18%	9.34%
1990	105	0.34%	2.21	1.59%	-3.94%	-0.07%	0.03%	0.39%	13.31%
1991	134	0.33%	1.56	2.45%	-6.05%	-0.26%	0.06%	0.51%	15.87%
1992	118	0.11%	0.27	4.26%	-32.87%	-0.02%	0.15%	0.89%	7.72%
1993	182	0.81%	3.98	2.75%	-5.54%	-0.11%	0.18%	1.04%	26.74%
1994	176	0.41%	2.92	1.87%	-5.05%	-0.15%	0.06%	0.74%	13.10%
1995	193	0.25%	1.94	1.82%	-9.36%	-0.10%	0.11%	0.52%	8.91%
Overall	1517	0.24%	4.25	2.16%	-32.87%	-0.07%	0.04%	0.35%	26.74%
Pre-1981	209	0.07%	2.61	0.37%	-1.13%	-0.01%	0.01%	0.06%	3.41%
Post-1980	1308	0.26%	4.10	2.32%	-32.87%	-0.09%	0.07%	0.46%	26.74%

The change in Relative Short Interest is the computed over two months for all stocks and over one month for stocks with options introduced on the 1st or after the 14th of the option listing month. Two month changes are computed as Delta RSI=(SI+1 less SI-1)/Shares outstanding.

Table 5-4
Percentage Change in Relative Short Interest–One vs. Two Months (Post-1980 Introductions)

Months	Listings	Delta RSI	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
	PANEL A: All stocks, call-only and joint listings								
2	741	0.20%	2.1525	2.58%	-32.87%	-0.11%	0.05%	0.47%	15.87%
1	745	0.11%	2.4106	1.23%	-7.63%	-0.11%	0.03%	0.23%	12.05%
	F Stat p-value equals 0.00000000								
	PANEL B: All stocks, call-only listings								
2	170	0.02%	0.3542	0.75%	-5.61%	-0.08%	0.04%	0.19%	3.62%
1	172	0.01%	0.2245	0.56%	-3.09%	-0.08%	0.02%	0.15%	4.03%
	F Stat p-value equals 0.00007463								
	PANEL C: All stocks, joint listings								
2	571	0.26%	2.1249	2.91%	-32.87%	-0.11%	0.06%	0.63%	15.87%
1	573	0.14%	2.4223	1.37%	-7.63%	-0.14%	0.03%	0.28%	12.05%
	F Stat p-value equals 0.00000000								
	PANEL D: NYSE stocks, call-only and joint listings								
2	406	0.04%	0.3034	2.52%	-32.87%	-0.08%	0.03%	0.21%	13.31%
1	407	0.05%	1.2318	0.84%	-7.63%	-0.07%	0.01%	0.15%	6.08%
	F Stat p-value equals 0.00000000								
	PANEL E: AMEX stocks, call-only and joint listings								
2	30	-0.15%	-0.5509	1.49%	-5.86%	-0.35%	-0.04%	0.24%	2.82%
1	29	0.04%	0.1878	1.24%	-3.18%	-0.40%	0.02%	0.19%	3.87%
	F Stat p-value equals 0.16585927								
	PANEL F: NASD stocks, call-only and joint listings								
2	305	0.46%	2.9487	2.73%	-24.69%	-0.13%	0.15%	0.98%	15.87%
1	309	0.19%	2.0854	1.60%	-6.41%	-0.22%	0.08%	0.49%	12.05%
	F Stat p-value equals 0.00000000								

This table compares the two month change in short interest to the one month change in short interest for listings that occur on the 15th day of the month or later. The Reported F Statistic p-value is the probability of variance equality across the two samples. Two month changes are computed as Delta RSI=(SI+1 less SI-1)/Shares Outstanding. One month changes are computed as Delta RSI=(SI+1 less SI=0)/Shares Outstanding.

Table 5-5
Percentage Increase in Short Interest (% Increase = SI(t+1)/SI(t-1)-1)

PANEL A: All stocks, call-only and joint listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973-1980	209	102.0%	3.8848	379.6%	-97.3%	-18.1%	17.0%	107.3%	4644.5%
1981-1995	1308	95.4%	11.6242	296.8%	-100.0%	-17.2%	16.5%	80.9%	3611.5%

PANEL B: All stocks, call-only listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973-1980	205	102.6%	3.834	383.1%	-97.3%	-18.1%	16.4%	107.3%	4644.5%
1981-1995	282	95.4%	5.188	308.9%	-93.1%	-17.9%	15.0%	85.7%	3611.5%

PANEL C: All stocks, joint listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973-1980	4	72.6%	1.3751	105.6%	-28.3%	-11.0%	48.9%	180.0%	221.1%
1981-1995	1026	95.4%	10.4082	293.6%	-100.0%	-17.1%	16.9%	79.4%	3034.4%

PANEL D: NYSE stocks, call-only and joint listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973-1980	205	104.4%	3.9026	382.9%	-97.3%	-17.9%	17.6%	108.6%	4644.5%
1981-1995	690	101.7%	8.2471	324.0%	-100.0%	-25.5%	14.1%	90.0%	3611.5%

PANEL E: AMEX stocks, call-only and joint listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973-1980	4	-18.9%	-0.9216	41.0%	-71.0%	-58.8%	-16.6%	18.7%	28.7%
1981-1995	53	36.0%	2.4786	105.8%	-60.5%	-14.1%	0.1%	67.9%	624.3%

PANEL F: NASD stocks, call-only and joint listings

Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1981-1995	565	93.3%	8.1204	273.0%	-99.5%	-11.1%	20.8%	77.3%	2827.2%

Table 5-5--Continued

PANEL G: All stocks, call-only and joint listings, by year									
Years	Listings	Mean% Increase	T-Stat	Stand Dev	Minimum	25th %	Median	75th %	Maximum
1973	18	11.5%	0.848989	57.7%	-87.7%	-24.0%	-0.9%	64.3%	124.7%
1974	6	18.3%	0.522849	85.8%	-67.1%	-50.1%	-6.4%	93.7%	163.9%
1975	80	115.8%	1.936676	534.8%	-97.3%	-16.8%	7.2%	95.9%	4644.5%
1976	47	141.6%	3.103704	312.7%	-97.0%	-29.9%	35.2%	183.6%	1609.9%
1977	13	127.4%	1.159882	396.1%	-73.4%	-52.9%	-10.1%	94.0%	1387.3%
1978	5	125.9%	1.59722	176.3%	-38.6%	-20.1%	77.1%	296.5%	397.6%
1979	0								
1980	40	69.9%	4.115018	107.5%	-71.0%	-9.3%	45.2%	114.8%	434.6%
1981	9	-11.3%	-0.78465	43.4%	-74.6%	-52.1%	-9.5%	30.6%	46.5%
1982	70	83.1%	2.803939	248.0%	-82.2%	-26.5%	9.8%	70.5%	1543.5%
1983	22	14.0%	0.914906	71.7%	-49.3%	-29.6%	-7.7%	22.8%	257.9%
1984	10	105.7%	1.882323	177.6%	-56.1%	-0.8%	33.5%	198.0%	538.4%
1985	30	219.0%	1.765135	679.5%	-93.1%	-5.7%	41.8%	172.0%	3611.5%
1986	18	158.5%	1.737518	387.1%	-61.9%	-40.8%	6.9%	140.1%	1261.7%
1987	95	78.7%	3.676584	208.6%	-91.1%	-22.6%	14.1%	103.8%	1579.6%
1988	76	91.1%	2.211053	359.0%	-95.4%	-7.9%	30.4%	80.8%	3034.4%
1989	70	51.6%	3.224606	133.9%	-95.2%	-24.7%	14.6%	91.4%	624.3%
1990	105	62.2%	3.600092	177.1%	-100.0%	-18.9%	11.0%	60.4%	1064.9%
1991	134	70.2%	3.828129	212.3%	-92.2%	-20.2%	12.7%	68.9%	1264.3%
1992	118	150.3%	3.657826	446.4%	-99.0%	-10.2%	19.2%	97.2%	2839.6%
1993	182	120.8%	5.361508	303.9%	-99.0%	-12.8%	39.0%	114.4%	2025.7%
1994	176	72.4%	4.881608	196.7%	-94.3%	-16.3%	10.2%	54.4%	1074.7%
1995	193	113.4%	4.680781	336.5%	-99.5%	-23.7%	16.5%	89.4%	2143.1%

This table shows the percentage increase in short interest levels occurring between the short interest report in the month preceding the option listing date and the report for the subsequent month. Thus, each increase is over a two month period.

Table 5-6
Model 1: Explaining Abnormal Returns

PANEL A

Dependent Variable	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375	-0.4518	-0.4518
Standard Error	5.0143	5.0219	5.0266	5.0394	5.0179	5.0210	4.6544	4.6634
R-Squared	0.1538	0.1512	0.1496	0.1452	0.1525	0.1515	0.1071	0.1036
Adjusted R-Squared	0.1514	0.1488	0.1472	0.1428	0.1502	0.1491	0.1029	0.0994
F-statistic	64.54	63.28	62.49	60.37	63.95	63.43	25.54	24.62
Log of the Li'hood Func.	-4769.12	-4771.28	-4772.63	-4776.25	-4770.13	-4771.02	-2782.26	-2783.92
CONSTANT	1.793784	1.677515	1.507127	1.321891	1.587911	1.647858	0.841832	0.568071
	4.60 **	4.28 **	3.90 **	3.42 **	4.46 **	4.26 **	1.96 *	1.34
BETA1	-0.663807		-0.892001		-0.941295		-0.82542	
	-2.47 **		-3.45 **		-3.95 **		-2.49 **	
SUMBETA		-0.29329		-0.462369		-0.362905		-0.479197
		-1.32		-2.11 *		-1.71 *		-1.77 *
SDR1	-53.329292	-64.21846						
	-2.91 **	-3.58 **						
SDR5			-13.438387	-17.932121				
			-1.66 *	-2.20 *				
SDEBW					-100.68563			
					-2.70 **			
SDESUMB						-64.908654		
						-3.59 **		
IBES							0.0001	0.000046
							0.22	0.10
ABVOL	0.239955	0.229068	0.251807	0.239489	0.283341	0.231278	0.174856	0.169789
	4.35 **	4.13 **	4.43 **	4.18 **	4.96 **	4.18 **	2.34 **	2.24 *
ALPHA	-7.839427	-7.726359	-8.052516	-7.933733	-8.447623	-7.680049	-7.77788	-7.781609
	-11.56 **	-11.33 **	-11.84 **	-11.54 **	-13.46 **	-11.16 **	-8.57 **	-8.54 **

Table 5-6--Continued

PANEL B

Dependent Variable	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425	-0.2467	-0.2467
Standard Error	3.3815	3.3822	3.3826	3.3838	3.3778	3.3815	3.0875	3.0883
R-Squared	0.0592	0.0589	0.0587	0.0580	0.0613	0.0592	0.0335	0.0330
Adjusted R-Squared	0.0566	0.0562	0.0560	0.0553	0.0586	0.0566	0.0290	0.0285
F-statistic	22.37	22.22	22.13	21.86	23.20	22.37	7.39	7.27
Log of the Li'hood Func.	-4301.77	-4302.05	-4302.22	-4302.73	-4300.22	-4301.77	-2492.61	-2492.83
CONSTANT	0.5636	0.5333	0.5315	0.4787	0.5560	0.5334	0.2489	0.1807
	2.20 *	2.08 *	2.11 *	1.91 *	2.50 **	2.14 *	0.97	0.75
BETA1	-0.1698		-0.2264		-0.2718		-0.2162	
	-0.93		-1.29		-1.64		-0.99	
SUMBETA		-0.0742		-0.1102		-0.0936		-0.1287
		-0.50		-0.75		-0.65		-0.72
SDR1	-22.0417	-24.8436						
	-1.82 *	-2.13 *						
SDR5			-8.5323	-9.7335				
			-1.61	-1.86 *				
SDEBW					-54.0464			
					-2.50 **			
SDESUMB						-26.2291		
						-2.27 *		
IBES							-0.0004	-0.0004
							-1.32	-1.37
ABVOL	0.0727	0.0702	0.0743	0.0713	0.1034	0.0709	0.0341	0.0326
	2.19 *	2.12 *	2.28 *	2.19 *	3.10 **	2.14 *	0.86	0.82
ALPHA	-3.3570	-3.3262	-3.3585	-3.3243	-3.6554	-3.2902	-2.8159	-2.8111
	-7.85 **	-7.79 **	-7.62 **	-7.55 **	-8.92 **	-7.63 **	-5.03 **	-5.00 **

Table 5-6--Continued

PANEL C

Dependent Variable	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	0.0046	0.0046	0.0046	0.0046	0.0046	0.0046	0.0089	0.0089
Standard Error	0.4541	0.4548	0.4553	0.4565	0.4545	0.4547	0.4224	0.4232
R-Squared	0.0513	0.0484	0.0463	0.0414	0.0499	0.0488	0.0322	0.0288
Adjusted R-Squared	0.0486	0.0457	0.0436	0.0387	0.0472	0.0461	0.0276	0.0242
F-statistic	19.20	18.06	17.25	15.35	18.66	18.23	7.08	6.30
Log of the Li'hood Func.	-1344.40	-1346.55	-1348.11	-1351.76	-1345.42	-1346.24	-725.82	-727.34
CONSTANT	0.166703	0.156362	0.140776	0.1241	0.147555	0.153728	0.077218	0.054751
	4.68 **	4.37 **	3.99 **	3.52 **	4.54 **	4.35 **	1.96 *	1.42
BETA1	-0.0608		-0.0817		-0.0870		-0.0757	
	-2.49 **		-3.48 **		-4.02 **		-2.50 **	
SUMBETA		-0.0275		-0.0429		-0.0340		-0.0464
		-1.38		-2.18 *		-1.78 *		-1.89 *
SDR1	-5.0712	-6.0471						
	-3.06 **	-3.71 **						
SDR5			-1.3286	-1.7328				
			-1.81 *	-2.34 **				
SDEBW					-9.6738			
					-2.88 **			
SDESUMB						-6.1247		
						-3.73 **		
IBES							0.0000	
							0.11	
ABVOL	0.0224	0.0214	0.0234	0.0223	0.0265	0.0216	0.0162	0.0157
	4.39 **	4.17 **	4.46 **	4.22 **	5.04 **	4.22 **	2.39 **	2.29 *
ALPHA	0.2884	0.2985	0.2695	0.2802	0.2305	0.3030	0.2907	0.2907
	4.70 **	4.84 **	4.38 **	4.51 **	4.05 **	4.87 **	3.53 **	3.51 **

PANEL D

Table 5-6--Continued

PANEL D

Dependent Variable	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009	-0.0039	-0.0039
Standard Error	0.5663	0.5664	0.5668	0.5669	0.5665	0.5662	0.5169	0.5171
R-Squared	0.0337	0.0335	0.0324	0.0317	0.0331	0.0342	0.0391	0.0385
Adjusted R-Squared	0.0310	0.0308	0.0296	0.0290	0.0304	0.0315	0.0346	0.0340
F-statistic	12.40	12.31	11.88	11.62	12.15	12.58	8.67	8.52
Log of the Li'hood Func.	-1753.30	-1753.49	-1754.33	-1754.82	-1753.80	-1752.96	-960.94	-961.24
CONSTANT	0.113207	0.108428	0.105069	0.095796	0.091292	0.10817	0.036959	0.024091
	2.65 **	2.53 **	2.49 **	2.29 *	2.44 **	2.60 **	0.86	0.59
BETA1	-0.0211		-0.0355		-0.0528		-0.0420	
	-0.69		-1.21		-1.90 *		-1.15	
SUMBETA		-0.0072		-0.0158		-0.0120		-0.0254
		-0.29		-0.64		-0.50		-0.85
SDR1	-5.5389	-5.9500						
	-2.77 **	-3.08 **						
SDR5			-2.1381	-2.3447				
			-2.42 **	-2.68 **				
SDEBW					-9.4092			
					-2.65 **			
SDESUMB						-6.2598		
						-3.27 **		
IBES							-0.0001	-0.0001
							-1.35	-1.40
ABVOL	0.0133	0.0130	0.0137	0.0132	0.0194	0.0131	0.0075	0.0072
	2.37 **	2.31 *	2.49 **	2.40 **	3.45 **	2.35 **	1.13	1.08
ALPHA	0.4322	0.4368	0.4318	0.4377	0.3617	0.4451	0.5190	0.5200
	6.05 **	6.12 **	5.88 **	5.95 **	5.24 **	6.19 **	5.53 **	5.52 **

Table 5-6--Continued

PANEL E

Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	0.1275	0.1275	0.1275	0.1275	0.1275	0.1275	-0.0625	-0.0625
Standard Error	7.2909	7.2931	7.2907	7.2933	7.1778	7.2910	6.6370	6.6375
R-Squared	0.0131	0.0125	0.0131	0.0124	0.0435	0.0131	0.0175	0.0174
Adjusted R-Squared	0.0103	0.0097	0.0104	0.0096	0.0408	0.0103	0.0129	0.0128
F-statistic	4.70	4.49	4.73	4.47	16.14	4.70	3.80	3.77
Log of the Li'hood Func.	-5126.95	-5127.37	-5126.90	-5127.41	-5104.64	-5126.96	-2974.85	-2974.92
CONSTANT	1.29852	1.280899	1.280112	1.223397	2.667308	1.35554	0.138237	0.09106
	2.07 *	2.10 *	2.06 *	2.06 *	3.19 **	2.25 *	0.25	0.17
BETA1	-0.7600		-0.7855		-0.6840		-0.4565	
	-1.92 *		-2.14 *		-1.74 *		-1.11	
SUMBETA		-0.5486		-0.5757		-0.5410		-0.3577
		-1.54		-1.71 *		-1.58		-0.97
SDR1	-24.7724	-30.7915						
	-0.90	-1.07						
SDR5			-11.6965	-13.6993				
			-1.00	-1.09				
SDEBW					-275.6206			
					-2.09 *			
SDESUMB						-38.9575		
						-1.32		
IBES							0.0007	0.0006
							1.13	1.07
ABVOL	0.0905	0.0883	0.0923	0.0903	0.2270	0.0917	-0.2573	-0.2577
	0.42	0.42	0.43	0.43	1.43	0.43	-0.64	-0.65
ALPHA	2.5381	2.6543	2.5916	2.7062	2.3408	2.7433	2.2155	2.2746
	2.60 **	2.74 **	2.64 **	2.77 **	2.48 **	2.82 **	1.89 *	1.94 *

Table 5-6--Continued

PANEL F

Dependent Variable	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	-0.0591	-0.0591
Standard Error	5.4364	5.4357	5.4366	5.4357	5.4173	5.4342	4.7609	4.7609
R-Squared	0.0170	0.0173	0.0169	0.0173	0.0239	0.0178	0.0109	0.0109
Adjusted R-Squared	0.0142	0.0145	0.0141	0.0145	0.0211	0.0150	0.0063	0.0062
F-statistic	6.14	6.24	6.11	6.24	8.69	6.43	2.35	2.34
Log of the Li'hood Func.	-4708.40	-4708.20	-4708.46	-4708.21	-4703.39	-4707.82	-2690.13	-2690.15
CONSTANT	0.342131	0.410876	0.300505	0.388879	0.695224	0.501571	-0.249236	-0.116421
	0.82	0.99	0.71	0.93	1.63	1.24	-0.68	-0.33
BETA1	0.0486		0.0126		-0.0162		0.0805	
	0.15		0.04		-0.06		0.26	
SUMBETA		-0.1520		-0.1625		-0.1271		-0.0517
		-0.59		-0.68		-0.52		-0.20
SDR1	-21.4047	-13.7224						
	-1.00	-0.67						
SDR5			-9.1040	-6.2395				
			-1.02	-0.70				
SDEBW					-102.6336			
					-1.73 *			
SDESUMB						-21.8166		
						-1.10		
IBES							0.0001	0.0001
							0.11	0.19
ABVOL	0.1450	0.1468	0.1465	0.1477	0.1963	0.1487	-0.0340	-0.0329
	1.51	1.53	1.53	1.55	2.27 *	1.56	-0.43	-0.41
ALPHA	2.2729	2.2316	2.2977	2.2574	2.1027	2.3068	2.4414	2.4537
	3.17 **	3.14 **	3.16 **	3.12 **	3.02 **	3.22 **	2.80 **	2.82 **

Table 5-6--Continued

I estimate the following regression

(1) $AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 ABVOL + \alpha_4 ALPHA$

For the sample of post-1980 option introductions where the abnormal return dependent variable is either

BWCAR11	Brown and Warner CARs over an 11 day window
BWCAR6	Brown and Warner CARs over an 6 day window
NOALPH11	Brown and Warner CARs with $\alpha=0$ (11 days)
NOALPH6	Brown and Warner CARs with $\alpha=0$ (6 days)
ABRET11	Stock return less Market Return over 11 days
ABRET6	Stock return less Market Return over 6 days

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are either

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

All t-statistics are computed using White's heteroskedasticity correction.

Table 5-7
Models 2 and 3: Explaining Abnormal Returns with Purging Regressions

PANEL A

Dependent Variable	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375	-0.7375
Standard Error	5.0143	5.0394	5.0179	5.0210	5.0143	5.0171	5.0179	5.0210
R-Squared	0.1538	0.1452	0.1525	0.1515	0.1538	0.1528	0.1525	0.1515
Adjusted R-Squared	0.1514	0.1428	0.1502	0.1491	0.1514	0.1504	0.1502	0.1491
F-statistic	64.54	60.37	63.95	63.43	64.54	64.07	63.95	63.43
Log of the Li'hood Func.	-4769.12	-4776.25	-4770.13	-4771.02	-4769.12	-4769.93	-4770.13	-4771.02
	Model 2				Model 3			
CONSTANT	1.605013	1.017495	0.580529	1.423339	0.783797	2.584561	0.885329	3.150701
	4.22 **	2.73 **	1.97 *	3.87 **	2.51 **	4.11 **	2.87 **	2.96 **
SDR1	-76.607265							
	-4.84 **							
SDR5		-24.165122						
		-3.27 **						
SDEBW			-124.650519					
			-3.40 **					
SDESUMB				-76.63085				
				-4.59 **				
BETA1					-1.068937		-1.079191	
					-4.59 **		-4.62 **	
SUMBETA						-117.13193		-141.913867
						-4.76 **		-3.41 **
RES(BETA1)	-0.663807		-0.941295					
	-2.47 **		-3.95 **					
RES(SUMBETA)		-0.462369		-0.362905				
		-2.11 *		-1.71 *				

Table 5-7--Continued

Dependent Variable	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11	BWCAR11
RES(SDR1)					-53.329293			
					-2.91**			
RES(SDR5)						26.520665		
						2.21*		
RES(SDEBW)							-100.68563	
							-2.70**	
RES(SDESUMB)								77.005214
								1.71*
ABVOL	0.239955	0.239489	0.283341	0.231278	0.239955	0.237553	0.283341	0.231278
	4.35**	4.18**	4.96**	4.18**	4.35**	4.25**	4.96**	4.18**
ALPHA	-7.839427	-7.933733	-8.447623	-7.680049	-7.839427	-7.816101	-8.447623	-7.680049
	-11.56**	-11.54**	-13.46**	-11.16**	-11.56**	-11.38**	-13.46**	-11.16**

Table 5-7--Continued

PANEL B

Dependent Variable	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425	-0.3425
Standard Error	3.3815	3.3838	3.3778	3.3815	3.3815	3.3818	3.3778	3.3815
R-Squared	0.0592	0.0580	0.0613	0.0592	0.0592	0.0591	0.0613	0.0592
Adjusted R-Squared	0.0566	0.0553	0.0586	0.0566	0.0566	0.0564	0.0586	0.0566
F-statistic	22.37	21.86	23.20	22.37	22.37	22.30	23.20	22.37
Log of the Li'hood Func.	-4301.77	-4302.73	-4300.22	-4301.77	-4301.77	-4301.91	-4300.22	-4301.77
	Model 2				Model 3			
CONSTANT	0.515285	0.406157	0.265082	0.475548	0.146119	0.605831	0.178854	0.920893
	2.09 *	1.73 *	1.55	2.06 *	0.72	1.48	0.90	1.26
SDR1	-27.99478							
	-2.60 **							
SDR5		-1.21920						
		-2.28 *						
SDEBW			-60.9668					
			-2.87 **					
SDESUMB				-29.2513				
				-2.65 **				
BETA1					-0.337206		-0.345843	
					-2.08 *		-2.12 *	
SUMBETA						-33.61115		-46.0824
						-2.05 *		-1.58
RES(BETA1)	-0.16976		-0.271823					
	-0.93		-1.64					
RES(SUMBETA)		-0.110208		-0.093564				
		-0.75		-0.65				
RES(SDR1)					-22.0417			
					-1.82 *			

Table 5-7--Continued

Dependent Variable	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6	BWCAR6
RES(SDR5)						3.045295		
						0.39		
RES(SDEBW)							-54.0463	
							-2.50 **	
RES(SDESUMB)								19.8533
								0.65
ABVOL	0.072724	0.071331	0.103433	0.070885	0.072724	0.070548	0.103433	0.070885
	2.19 *	2.19 *	3.10 **	2.14 *	2.19 *	2.13 *	3.10 **	2.14 *
ALPHA	-3.357012	-3.324282	-3.65541	-3.290248	-3.357012	-3.290032	-3.65541	-3.290248
	-7.85 **	-7.55 **	-8.92 **	-7.63 **	-7.85 **	-7.47 **	-8.92 **	-7.63 **

Table 5-7--Continued

PANEL C

Dependent Variable	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	0.0046	0.0046	0.0046	0.0046	0.0046	0.0046	0.0046	0.0046
Standard Error	0.4541	0.4565	0.4545	0.4547	0.4541	0.4544	0.4545	0.4547
R-Squared	0.0513	0.0414	0.0499	0.0488	0.0513	0.0501	0.0499	0.0488
Adjusted R-Squared	0.0486	0.0387	0.0472	0.0461	0.0486	0.0474	0.0472	0.0461
F-statistic	19.20	15.35	18.66	18.23	19.20	18.73	18.66	18.23
Log of the Li'hood Func.	-1344.40	-1351.76	-1345.42	-1346.24	-1344.40	-1345.28	-1345.42	-1346.24
	Model 2				Model 3			
CONSTANT	0.149422	0.095884	0.054442	0.132716	0.070662	0.237476	0.080051	0.294376
	4.30 **	2.82 **	2.04 *	3.95 **	2.49 **	4.17 **	2.85 **	3.07 **
SDR1	-7.202234							
	-5.00 **							
SDR5		-2.310567						
		-3.44 **						
SDEBW			-11.888916					
			-3.60 **					
SDESUMB				-7.221739				
				-4.76 **				
BETA1					-0.099295		-0.100254	
					-4.70 **		-4.73 **	
SUMBETA						-10.872651		-13.331444
						-4.89 **		-3.55 **
RES(BETA1)	-0.06077		-0.087005					
	-2.49 **		-4.02 **					
RES(SUMBETA)		-0.04286		-0.033964				
		-2.18 *		-1.78 *				
RES(SDR1)					-5.07118			
					-3.06 **			

Table 5-7--Continued

Dependent Variable	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11	NOALPH11
RES(SDR5)						2.393145		
						2.21 *		
RES(SDEBW)							-9.673825	
							-2.88 **	
RES(SDESUMB)								7.206761
								1.78 *
ABVOL	0.022358	0.022306	0.026498	0.02158	0.022358	0.022117	0.026498	0.02158
	4.39 **	4.22 **	5.04 **	4.22 **	4.39 **	4.29 **	5.04 **	4.22 **
ALPHA	0.288373	0.280219	0.230514	0.303044	0.288373	0.291084	0.230514	0.303044
	4.70 **	4.51 **	4.05 **	4.87 **	4.70 **	4.68 **	4.05 **	4.87 **

Table 5-7--Continued

PANEL D

Dependent Variable	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009	-0.0009
Standard Error	0.5663	0.5669	0.5665	0.5662	0.5663	0.5662	0.5665	0.5662
R-Squared	0.0337	0.0317	0.0331	0.0342	0.0337	0.0341	0.0331	0.0342
Adjusted R-Squared	0.0310	0.0290	0.0304	0.0315	0.0310	0.0314	0.0304	0.0315
F-statistic	12.40	11.62	12.15	12.58	12.40	12.54	12.15	12.58
Log of the Li'hood Func.	-1753.30	-1754.82	-1753.80	-1752.96	-1753.30	-1753.04	-1753.80	-1752.96
	Model 2				Model 3			
CONSTANT	0.107203	0.085426	0.034776	0.100753	0.008308	0.117085	0.025635	0.15782
	2.61 **	2.18 *	1.23	2.62 **	0.25	1.72 *	0.77	1.30
SDR1	-6.279301							
	-3.51 **							
SDR5		-2.557081						
		-3.12 **						
SDEBW			-10.753736					
			-3.07 **					
SDESUMB				-6.647035				
				-3.63 **				
BETA1					-0.063191		-0.065696	
					-2.32 *		-2.40 **	
SUMBETA						-7.192648		-8.803791
						-2.64 **		-1.82 *
RES(BETA1)	-0.021113		-0.052809					
	-0.69		-1.90 *					
RES(SUMBETA)		-0.015751		-0.011989				
		-0.64		-0.50				
RES(SDR1)					-5.538905			

Table 5-7--Continued

Dependent Variable	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6	NOALPH6
					-2.77 **			
RES(SDR5)						0.381913		
						0.29		
RES(SDEBW)							-9.409246	
							-2.65 **	
RES(SDESUMB)								2.544023
								0.50
ABVOL	0.013304	0.013222	0.019371	0.013131	0.013304	0.013085	0.019371	0.013131
	2.37 **	2.40 **	3.45 **	2.35 **	2.37 **	2.33 **	3.45 **	2.35 **
ALPHA	0.432242	0.437722	0.361694	0.445133	0.432242	0.445231	0.361694	0.445133
	6.05 **	5.95 **	5.24 **	6.19 **	6.05 **	6.07 **	5.24 **	6.19 **

Table 5-7--Continued

PANEL E

Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	0.1275	0.1275	0.1275	0.1275	0.1275	0.1275	0.1275	0.1275
Standard Error	7.2909	7.2933	7.1778	7.2910	7.2909	7.2953	7.1778	7.2910
R-Squared	0.0131	0.0124	0.0435	0.0131	0.0131	0.0119	0.0435	0.0131
Adjusted R-Squared	0.0103	0.0096	0.0408	0.0103	0.0103	0.0091	0.0408	0.0103
F-statistic	4.70	4.47	16.14	4.70	4.70	4.27	16.14	4.70
Log of the Li'hood Func.	-5126.95	-5127.41	-5104.64	-5126.96	-5126.95	-5127.81	-5104.64	-5126.96
	Model 2				Model 3			
CONSTANT	1.082401	0.844363	1.935265	1.020817	0.829362	2.095813	0.744035	3.596051
	1.79 *	1.47	2.17 *	1.72 *	1.70 *	2.20 *	1.41	2.17 *
SDR1	-51 422829							
	-2.13 *							
SDR5		-21.460603						
		-1.90 *						
SDEBW			-293.0353					
			-2.29 *					
SDESUMB				-56.433548				
				-2.18 *				
BETA1					-0.948167		-1.061502	
					-2.71 **		-2.97 **	
SUMBETA						-92.67538		-153.7606
						-2.53 **		-2.42 **
RES(BETA1)	-0.759976		-0.68402					
	-1.92 *		-1.74 *					
RES(SUMBETA)		-0.575742		-0.541037				
		-1.71 *		-1.58				
RES(SDR1)					-24.772429			
					-0.90			

Table 5-7--Continued

Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
RES(SDR5)						22.384372		
						1.25		
RES(SDEBW)							-275.62056	
							-2.09 *	
RES(SDESUMB)								114.8031
								1.58
ABVOL	0.090486	0.090288	0.226974	0.091695	0.090486	0.090353	0.226974	0.091695
	0.42	0.43	1.43	0.43	0.42	0.42	1.43	0.43
ALPHA	2.538099	2.706221	2.340806	2.743309	2.538099	2.689365	2.340806	2.743309
	2.60 **	2.77 **	2.48 **	2.82 **	2.60 **	2.74 **	2.48 **	2.82 **

Table 5-7--Continued

PANEL F

Dependent Variable	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6
# of Observations	1426	1426	1426	1426	1426	1426	1426	1426
Mean of Dep. Var.	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676	0.0676
Standard Error	5.4364	5.4357	5.4173	5.4342	5.4364	5.4338	5.4173	5.4342
R-Squared	0.0170	0.0173	0.0239	0.0178	0.0170	0.0179	0.0239	0.0178
Adjusted R-Squared	0.0142	0.0145	0.0211	0.0150	0.0142	0.0152	0.0211	0.0150
F-statistic	6.14	6.24	8.69	6.43	6.14	6.48	8.69	6.43
Log of the Li'hood Func.	-4708.40	-4708.21	-4703.39	-4707.82	-4708.40	-4707.72	-4703.39	-4707.82
	Model 2				Model 3			
CONSTANT	0.355966	0.281872	0.677908	0.422961	-0.063246	0.884777	-0.020951	1.027753
	0.88	0.71	1.64	1.11	-0.17	1.22	-0.06	0.85
SDR1	-19.698763							
	-1.12							
SDR5		-8.430599						
		-1.04						
SDEBW			-103.0455					
			-1.81 *					
SDESUMB				-25.920786				
				-1.45				
BETA1					-0.113958		-0.156744	
					-0.44		-0.61	
SUMBETA						-41.541739		-48.777967
						-1.47		-1.05
RES(BETA1)	0.048648		-0.01618					
	0.15		-0.06					
RES(SUMBETA)		-0.16254		-0.127062				
		-0.68		-0.52				
RES(SDR1)					-21.404732			
					-1.00			

Table 5-7--Continued

Dependent Variable	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6	ABRET6
RES(SDR5)						9.851995		
						0.70		
RES(SDEBW)							-102.6335	
							-1.73 *	
RES(SDESUMB)								26.961409
								0.52
ABVOL	0.145009	0.147722	0.196304	0.148656	0.145009	0.148778	0.196304	0.148656
	1.51	1.55	2.27 *	1.56	1.51	1.56	2.27 *	1.56
ALPHA	2.272928	2.257386	2.102655	2.306818	2.272928	2.263743	2.102655	2.306818
	3.17 **	3.12 **	3.02 **	3.22 **	3.17 **	3.14 **	3.02 **	3.22 **

I estimate the following two purging regression models

Model 2: Purging BETA on σ_ε

(2) $AR = \alpha_0 + \alpha_1 \varepsilon + \alpha_2 \sigma_\varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA + \gamma$

(3) $BETA = \beta_0 + \beta_1 \sigma_\varepsilon + \varepsilon$

Model 3: Purging σ_ε on BETA

(4) $AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA + \gamma$

(5) $\sigma_\varepsilon = \beta_0 + \beta_1 BETA + \varepsilon$

for the sample of post-1980 option introductions where the abnormal return dependent variable is either

BWCAR11	Brown and Warner CARs over an 11 day window
BWCAR6	Brown and Warner CARs over an 6 day window
NOALPH11	Brown and Warner CARs with α=0 (11 days)
NOALPH6	Brown and Warner CARs with α=0 (6 days)
ABRET11	Stock return less Market Return over 11 days
ABRET6	Stock return less Market Return over 6 days

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

Table 5-7--Continued

σ_E =a proxy for dispersion of expectations. The five alternative proxies are either

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

All t-statistics are computed using White's heteroskedasticity correction.

Table 5-8
Models 4 and 5: Detailing Volume Anomaly

	Model 4: SDESUMB			Model 5: SUMBETA		
Dependent Variable	Full Sample ABRET11	Low Volume ABRET11	High Volume ABRET11	Full Sample ABRET11	Low Volume ABRET11	High Volume ABRET11
# of Observations	1426	1263	163	1426	1143	283
Mean of Dep. Var.	0.1275	0.1198	0.1729	0.1275	0.0683	0.3070
Standard Error	7.2966	7.3917	6.6362	7.2942	7.6210	6.1478
R-Squared	0.0108	0.0083	0.0731	0.0115	0.0102	0.0460
Adjusted R-Squared	0.0088	0.0059	0.0556	0.0094	0.0076	0.0357
F-statistic	5.20	3.50	4.18	5.51	3.93	4.48
Log of the Li'hood Func.	-5128.55	-4549.79	-574.68	-5128.09	-4144.54	-978.33
CONSTANT	1.07596	0.792475	2.22278	0.853323	0.581566	1.42998
	1.82 *	1.38	1.60	1.90 *	1.17	1.52
SDESUMB	-58.0416	-42.6348	-138.057			
	-2.24 *	-1.64	-1.90 *			
SUMBETA				-0.729193	-0.555512	-1.27088
				-2.43 **	-1.63	-1.94 *
ABVOL	0.088221	0.145033	-0.037217	0.088887	0.177141	-0.058319
	0.41	0.51	-0.16	0.42	0.56	-0.32
ALPHA	2.83749	1.86627	6.97866	2.43208	1.54335	4.63536
	2.91 **	1.83 *	2.54 **	2.58 **	1.37	2.42 **

I estimate the following two OLS models

Model 4: Explaining Abnormal Returns with dispersion proxies

(6) $ABRET11 = \alpha_0 + \alpha_1 SDESUMB + \alpha_2 ABVOL + \alpha_3 ALPHA$

Model 5: Explaining Abnormal Returns with BETA proxies

(7) $AR = \alpha_0 + \alpha_1 SUMBETA + \alpha_2 ABVOL + \alpha_3 ALPHA$

For the sample of post-1980 option introductions where the abnormal return dependent variable is

Table 5-8--Continued

ABRET11 Stock return less Market Return over 11 days

Independent Variables are:

SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6

SUMBETA sum of the coefficients on the market and lagged market return

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

These regressions bifurcate the full 1426 observation sample into high-trading-volume firms and low-trading-volume firms in order to demonstrate that most of the results obtained for the full sample result from inclusion of the high-trading-volume subset. The smaller sample for each model is composed of high-trading-volume firms. All t-statistics are computed using White's heteroskedasticity correction.

Table 5-9
Model 6: Explaining Ex-Ante Relative Short Interest

	Model 6							
Dependent Variable	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI
# of Observations	1335	1335	1334	1334	1335	1335	803	803
Mean of Dep. Var.	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0185	0.0185
Standard Error	0.0342	0.0342	0.0339	0.0340	0.0347	0.0341	0.0340	0.0341
R-Squared	0.0667	0.0658	0.0830	0.0815	0.0419	0.0733	0.0298	0.0275
Adjusted R-Squared	0.0653	0.0644	0.0816	0.0801	0.0405	0.0719	0.0274	0.0251
F-statistic	47.57	46.88	60.23	59.03	29.13	52.66	12.30	11.31
Log of the Li'hood Func.	2612.98	2612.34	2622.42	2621.32	2595.51	2617.73	1576.43	1575.46
CONSTANT	-0.002744	-0.002679	-0.002931	-0.002447	0.005359	-0.002747	0.007359	0.008002
	-1.19	-1.18	-1.36	-1.16	2.72 **	-1.27	2.79 **	2.98 **
BETA1	0.002608		0.00273		0.006801		0.007449	
	1.80 *		2.01 *		5.36 **		3.76 **	
SUMBETA		0.001645		0.001558		0.001935		0.005904
		1.35		1.35		1.64		3.45 **
SDR1	0.669469	0.699748						
	6.77 **	7.06 **						
SDR5			0.319461	0.331691				
			7.78 **	7.96 **				
SDEBW					0.671747			
					3.70 **			
SDESUMB						0.746445		
						7.57 **		
IBES							0.000005	0.000005
							1.45	1.56

I estimate the following model

(8) $\mathbf{EARSI} = \alpha_0 + \alpha_1 \mathbf{BETA} + \alpha_2 \sigma_\varepsilon + \tau$

Table 5-9--Continued

for the sample of post-1980 option introduetions where short interest data is available. The dependent variable, ex-ante relative short interest, is defined as

EARSI=Short Interest prior to the option introduetion divided by outstanding shares.

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

One observation has insufficient return data to compute a standard deviation for SDR5, and regressions using SDR5 as an independent variable have 1 fewer observations than regressions using SDEBW, SDESUMB, or SDR1. All t-statistics are computed using White's heteroskedasticity correction.

Table 5-10
Models 7 and 8: Explaining EARSI with Purging Regressions

	Model 7				Model 8			
Dependent Variable	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI
# of Observations	1335	1334	1335	1335	1335	1334	1335	1335
Mean of Dep. Var.	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200	0.0200
Standard Error	0.0342	0.0340	0.0347	0.0341	0.0342	0.0340	0.0347	0.0341
R-Squared	0.0667	0.0815	0.0419	0.0733	0.0667	0.0815	0.0419	0.0733
Adjusted R-Squared	0.0653	0.0801	0.0405	0.0719	0.0653	0.0801	0.0405	0.0719
F-statistic	47.57	59.03	29.13	52.66	47.57	59.03	29.13	52.66
Log of the Li'hood Func.	2612.98	2621.32	2595.51	2617.73	2612.98	2621.32	2595.51	2617.73
CONSTANT	-0.002002	-0.001422	0.012638	-0.00155	0.009935	0.011917	0.010047	0.011821
	-0.88	-0.69	7.71 **	-0.73	6.11 **	7.53 **	6.15 **	7.42 **
SDR1	0.760909							
	8.87 **							
SDR5		0.352693						
		9.35 **						
SDEBW			0.844908					
			4.74 **					
SDESUMB				0.808931				
				9.20 **				
BETA1					0.007693		0.007721	
					6.13 **		6.20 **	
SUMBETA						0.005435		0.005452
						5.23 **		5.20 **
RES(BETA1)	0.002608		0.006801					
	1.80 *		5.36 **					
RES(SUMBETA)		0.001558		0.001935				
		1.35		1.64				
RES(SDR1)					0.669469			

Table 5-10–Continued

Dependent Variable	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI	EARSI
					6.77 **			
RES(SDR5)						0.331691		
						7.96 **		
RES(SDEBW)							0.671747	
							3.70 **	
RES(SDESUMB)								0.746445
								7.57 **

I estimate the following two purging regression models

Model 7: Purging BETA on σ_E

(9) $\mathbf{EARSI} = \alpha_0 + \alpha_1 \varepsilon + \alpha_2 \sigma_E + \gamma$

(10) $\mathbf{BETA} = \beta_0 + \beta_1 \sigma_E + \varepsilon$

Model 8: Purging σ_E on BETA

(11) $\mathbf{EARSI} = \alpha_0 + \alpha_1 \mathbf{BETA} + \alpha_2 \varepsilon + \gamma$

(12) $\sigma_E = \beta_0 + \beta_1 \mathbf{BETA} + \varepsilon$

for the sample of post-1980 option introductions where short interest data is available. The dependent variable, ex-ante relative short interest, is defined as

EARSI=Short Interest prior to the option introduction divided by outstanding shares.

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

One observation has insufficient return data to compute a standard deviation for SDR5, and regressions using SDR5 as an independent variable have 1 fewer observations than regressions using SDEBW, SDESUMB, or SDR1. All t-statistics are computed using White's heteroskedasticity correction.

Table 5-11
Model 9: Explaining Changes in Relative Short Interest

	Model 9							
Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
# of Observations	1309	1309	1308	1308	1309	1309	787	787
Mean of Dep. Var.	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0020	0.0020
Standard Error	0.0162	0.0161	0.0162	0.0162	0.0163	0.0161	0.0112	0.0113
R-Squared	0.0908	0.0941	0.0879	0.0914	0.0823	0.0939	0.0360	0.0327
Adjusted R-Squared	0.0874	0.0906	0.0844	0.0879	0.0788	0.0905	0.0298	0.0265
F-statistic	26.04	27.06	25.09	26.19	23.37	27.02	5.84	5.29
Log of the Li'hood Func.	3473.90	3478.41	3468.38	3473.07	3467.84	3477.64	2415.63	2414.50
CONSTANT	-0.00385	-0.004103	-0.002803	-0.003078	-0.001502	-0.003839	-0.000435	-0.000123
	-3.19**	-3.35**	-2.26*	-2.55**	-1.08	-3.18**	-0.51	-0.14
BETA1	0.000789		0.001177		0.001903		0.00185	
	0.58		0.96		1.77*		2.43**	
SUMBETA		0.001296		0.001504		0.001447		0.001343
		1.49		1.83*		1.73*		1.96*
SDR1	0.191574	0.169504						
	2.69**	2.93**						
SDR5			0.065635	0.05869				
			2.66**	2.69**				
SDEBW					0.1784			
					1.67*			
SDESUMB						0.16521		
						2.88**		
IBES							0.000001	0.000001
							0.89	1.01
ALPHA	0.002609	0.002617	0.002658	0.002628	0.004782	0.00259	0.000645	0.000634
	1.26	1.18	1.22	1.15	1.89*	1.18	0.36	0.36
ONEMONTH	-0.001538	-0.001534	-0.001521	-0.00151	-0.001621	-0.001492	-0.000648	-0.000634
	-1.96*	-1.94*	-1.94*	-1.92*	-2.02*	-1.90*	-0.82	-0.80

Table 5-11–Continued

I estimate the following regression model

(13) $\Delta RSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 ABVOL + \alpha_4 ALPHA + \alpha_5 ONEMONTH$

for the sample of post-1980 option introductions with short interest data available. The dependent variable, the change in relative short interest, is defined as

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

ONEMONTH= a dummy for a one-month ΔRSI measurement window (1 month= 1, 2 months= 0)

All t-statistics are computed using White's heteroskedasticity correction.

Table 5-12
Models 10 and 11: Explaining ΔRSI with Purging Regressions

	Model 10				Model 11			
Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
# of Observations	1309	1308	1309	1309	1309	1308	1309	1309
Mean of Dep. Var.	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028
Standard Error	0.0162	0.0162	0.0163	0.0161	0.0162	0.0162	0.0163	0.0161
R-Squared	0.0908	0.0914	0.0823	0.0939	0.0908	0.0894	0.0823	0.0939
Adjusted R-Squared	0.0874	0.0879	0.0788	0.0905	0.0874	0.0859	0.0788	0.0905
F-statistic	26.04	26.19	23.37	27.02	26.04	25.58	23.37	27.02
Log of the Li'hood Func.	3473.90	3473.07	3467.84	3477.64	3473.90	3471.65	3467.84	3477.64
CONSTANT	-0.0036	-0.0021	0.0005	-0.0029	-0.0002	-0.0048	-0.0003	-0.0098
	-3.05 **	-1.98 *	0.63	-2.61 **	-0.17	-2.39 **	-0.19	-2.42 **
SDR1	0.2192							
	4.48 **							
SDR5		0.0790						
		3.97 **						
SDEBW			0.2269					
			2.15 *					
SDESUMB				0.2119				
				4.22 **				
BETA1					0.0022		0.0021	
					2.16 *		2.02 *	
SUMBETA						0.2798		0.4722
						3.42 **		2.98 **
RES(BETA1)	0.0008		0.0019					
	0.58		1.77 *					
RES(SUMBETA)		0.0015		0.0014				
		1.83 *		1.73 *				

Table 5-12–Continued

Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
RES(SDR1)					0.1916			
					2.69 **			
RES(SDR5)						-0.0387		
						-1.11		
RES(SDEBW)							0.1784	
							1.67 *	
RES(SDESUMB)								-0.3070
								-1.73 *
ABVOL	0.0008	0.0008	0.0007	0.0008	0.0008	0.0008	0.0007	0.0008
	2.71 **	2.80 **	2.59 **	2.78 **	2.71 **	2.74 **	2.59 **	2.78 **
ALPHA	0.0026	0.0026	0.0048	0.0026	0.0026	0.0028	0.0048	0.0026
	1.26	1.15	1.89 *	1.18	1.26	1.26	1.89 *	1.18
ONEMONTH	-0.0015	-0.0015	-0.0016	-0.0015	-0.0015	-0.0015	-0.0016	-0.0015
	-1.96 *	-1.92 *	-2.02 *	-1.90 *	-1.96 *	-1.85 *	-2.02 *	-1.90 *

I estimate the following two purging regression models

Model 10: Purging BETA on σ_E

(14) $\Delta RSI = \alpha_0 + \alpha_1 \varepsilon + \alpha_2 \sigma_E + \alpha_3 ABVOL + \alpha_4 ALPHA + \alpha_5 ONEMONTH + \gamma$

(15) $BETA = \beta_0 + \beta_1 \sigma_E + \varepsilon$

Model 11: Purging σ_E on BETA

(16) $\Delta RSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \varepsilon + \alpha_3 ABVOL + \alpha_4 ALPHA + \alpha_5 ONEMONTH + \gamma$

(17) $\sigma_E = \beta_0 + \beta_1 BETA + \varepsilon$

for the sample of post-1980 option introductions
with short interest data available. The dependent variable, the change in relative short interest, is defined as

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

Table 5-12–Continued

BETA1	a single market factor model
SUMBETA	sum of the coefficients on the market and lagged market return

σ_E=a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha from the Brown/Warner market model (days t-100 to t-6)

ONEMONTH= a dummy for a one-month ΔRSI measurement window (1 month= 1, 2 months= 0)

All t-statistics are computed using White's heteroskedasticity correction.

Table 5-13
Model 12: Examining ΔRSI and Abnormal Returns

	Model 12					
Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
# of Observations	1306	1306	1306	1306	1306	1306
Mean of Dep. Var.	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026
Standard Error	0.0157	0.0157	0.0158	0.0158	0.0158	0.0158
R-Squared	0.0681	0.0683	0.0620	0.0641	0.0614	0.0649
Adjusted R-Squared	0.0659	0.0661	0.0598	0.0620	0.0592	0.0628
F-statistic	31.70	31.80	28.67	29.73	28.37	30.13
Log of the Li'hood Func.	3510.97	3513.69	3504.05	3507.80	3503.00	3508.77
CONSTANT	0.266	0.2754	0.2914	0.2961	0.2944	0.2992
	4.198838 **	4.379739 **	4.32197 **	4.34232 **	4.323834 **	4.335827 **
BWCAR11	-0.183					
	-2.318169 *					
BWCAR6		-0.237				
		-1.79395 *				
NOALPH11			-0.1454			
			-1.781732 *			
NOALPH6				-0.1172		
				-1.541745		
ABRET11					-0.122	
					-1.692834 *	
ABRET6						-0.23
						-1.677276 *
ABVOL	0.89	0.81	0.822	0.823	0.82	0.822
	2.688265 **	2.685115 **	2.682685 **	2.65935 **	2.678311 **	2.6722 **
ONEMONTH	-0.146	-0.1497	-0.1514	-0.1551	-0.156	-0.155
	-1.763939 *	-1.838817 *	-1.851748 *	-1.867221 *	-1.845625 *	-1.869843 *

Table 5-13–Continued

I estimate the following regression model

(18) $\Delta RSI = \alpha_0 + \alpha_1 AR + \alpha_2 ABVOL + \alpha_3 ALPHA + \alpha_4 ONEMONTH$

for the sample of post-1980 option introductions with short interest data available. The dependent variable, the change in relative short interest, is defined as

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

Independent Variables are:

AR = abnormal returns as calculated using 6 methods discussed above

BWCAR11	Brown and Warner CARs over an 11 day window
BWCAR6	Brown and Warner CARs over an 6 day window
NOALPH11	Brown and Warner CARs with α=0 (11 days)
NOALPH6	Brown and Warner CARs with α=0 (6 days)
ABRET11	Stock return less Market Return over 11 days
ABRET6	Stock return less Market Return over 6 days

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ONEMONTH= a dummy for a one-month ΔRSI measurement window (1 month= 1, 2 months= 0)

All t-statistics are computed using White's heteroskedasticity correction.

CHAPTER 6
EMPIRICAL TESTS INCORPORATING SUPPLY CONSTRAINT PROXIES

Introduction

The purpose of this chapter is to extend the empirical results presented in Chapter 5 by presenting tests that allow for cross-sectional differences in the degree of short-sale constraint relaxation. To this point, neither the theoretical model developed in Chapter 4 nor the empirical tests presented in Chapter 5 have considered the possibility that option listings may produce different degrees of constraint relaxation in different firms. Obviously, if a firm is not short-sale constrained prior to the option introduction, we should not expect an option listing to produce any change in share price or short interest level.[1] By extension, firms that are less short-sale constrained ex-ante should see smaller share price declines and short interest increases than firms that are more constrained ex-ante.

The tests that follow in this chapter utilize proxy variables to measure the degree of short-sale constraint relaxation that results from an option introduction. These variables are used in tests with both abnormal return measures and relative short interest ("ΔRSI") as the left-hand-side variables. Before presenting the empirical tests, I will briefly discuss the theoretical underpinnings for these tests and the legitimacy of the proxy variables used.

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[1] This assumes that the identified option-short-sale link is the only connective present.

Theoretical Underpinnings

While intuition suggests that increasing the degree of constraint relaxation should increase the observed price and short-sale response, the mathematical model developed in Chapter 4 does not make this prediction. The graphical model, while offering support for intuition that the degree of constraint relaxation should matter, offers no further predictions about expected interactions between constraint relaxation and beta or dispersion of investor expectations. Let us consider why we are unable to craft stronger theoretical connections between the degree of constraint relaxation and the change in price and ΔRSI.

Recall from Chapter 4 that each investor optimized his expected utility by selecting investments subject to the constraint that he could not hold negative quantities of the short-sale-constrained security. All of the results produced in Chapter 4 depend upon an analysis of the effect this constraint has on share price and the impact that eliminating this constraint would have on subsequent short interest levels. Unfortunately, the model relies on an "all or nothing" constraint that implicitly precludes analysis where the constraint is relaxed in stages or where it is gradually relaxed. While I suspect that the model can be extended to allow for a gradual relaxation of the constraint, the existing model evaluates only a full and complete relaxation. Accordingly, the impact of partial or gradual constraint relaxation cannot be inferred from the model.

Although the mathematical model provides no guidance, we can gain some insights from the graphical model previously offered as Figure 5-1. Recall that in this figure, the degree of constraint relaxation is dependent upon the magnitude of C_S that represents the cost of short selling. Short sellers require a higher price to supply any aggregate quantity

of shares so that the S′ curve is the supply curve when the cost to sell short is C_s. The supply curve shifts to S when the short-sale constraint is removed (C_s=0). Obviously, if C_s is reduced, but not wholly eliminated, price and short interest will respond in the same direction, but in reduced magnitude. Notice that this testable implication is true for any negatively sloped demand curve.

Although the impact of partial relaxation is clear for any one firm, cross-sectional comparisons of firms remain ambiguous. Intuitively, we may suspect that many of the other results we have seen should be capable of incorporating the differential constraint relaxation extension. For example, one would be tempted to expect that since a wide range of investor share price expectations produces larger changes in short interest, this relationship should be even more pronounced when the constraint level has been relaxed more rather than less. Unfortunately, this result cannot be obtained from the graphical partial equilibrium model. In fact, notice from Figure 6-1 that the graphical model cannot even produce the result that short interest will rise more for high-dispersion-of-opinion firms than for low-dispersion-of-opinion firms. Figure 6-1 is a replication of Figure 5-1 with the addition of demand curve D″, which has a higher dispersion of investor opinion than curve D.[2] Notice that in this model, short interest actually increases less when demand curve D″ is used. In other words, the graph predicts that for two otherwise

[2] Recall that Miller (1977) develops its entire thesis around the assumption that the slope of the demand curve becomes steeper as the dispersion of investor opinion increases. Miller's discussion provides compelling arguments in support of this assumption. Further, Miller actually constructs a model where greater dispersion of expectations produces a steeper demand curve. In this model, each investor is limited to a single share of stock so that by increasing dispersion and holding the number of investors constant, the reservation price for the investors spread out to produce a more steeply sloped demand curve.

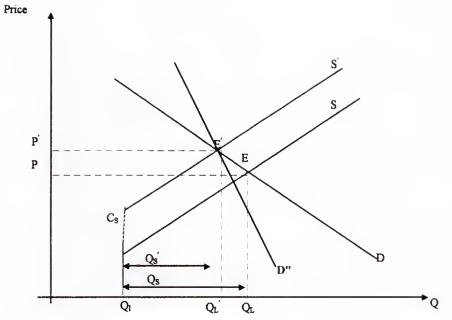

Figure 6-1. Partial Equilibrium Model of Demand Curve and Short-sale Effects When the Dispersion of Expectations Increases

identical firms, when dispersion of opinion is higher, short interest will be lower. This result contradicts the mathematical model previously presented in chapter 4. The contradiction results from the graphical model's failure to incorporate the dispersion of investor expectations in the slope of the supply curve. This shortcoming typifies the limitation inherent in a partial equilibrium model.

Obviously, if the graphical presentation cannot fully incorporate the impact of cross-sectional differences in dispersion of opinion, there is no hope that it can accommodate an interaction between dispersion of opinion and the degree of constraint relaxation. Thus, we are left without an explicit theoretical foundation for an hypothesis that, in cross-section, option listings which produce greater degrees of constraint level relaxation will generate greater price and short interest responses as a function of the exogenous variables, beta and dispersion of investor expectations. The only strong

assumption we can make is that price and short interest will change more for large constraint changes, but interactions among variables are not adequately foreseen.

Proxy Variables for Constraint Relaxation Levels

A second problem encountered when testing for the effects of cross-sectional constraint-relaxation differences is the difficulty in identifying reasonable proxies for the degree of constraint relaxation. Principally, I present two logical proxies although other less reasonable alternative proxies were also tested without success. The most obvious proxy is a dummy variable for joint put-call listings (PUT=1) versus call-only listings (PUT=0). The rationale for using this dummy as a measure of constraint relaxation is that trading of puts allows for better risk-return payoffs for bets against rising stock prices. The improved technology is unrelated to the degree by which investors speculate that the share is overpriced. Instead, the use of puts allows each pessimist to invest with greater potential gains and more limited losses. Specifically, buying puts produces virtually unlimited return potential and limited risk while writing calls produces limited returns with limitless risk. Thus, joint listings should produce greater constraint relaxation than call-only option introductions.

A major limitation of this PUT variable as a constraint relaxation proxy is that almost all of the call-only listings occur before 1988 while joint listings occur only in the later years of the study. Thus, PUT also functions as an "early year vs. recent year" proxy. An effort to control for this problem is discussed in the "Robustness Checks" later in this chapter.

The second constraint relaxation proxy presented is the value of the residual in Equation 8 of Chapter 5 that has been referred to as "τ" (tau). This residual can be

thought of as the portion of Ex-Ante Relative Short Interest ("EARSI") which is not explained by the two short-sale demand factors, beta and the dispersion of investor return expectations. When τ is small, short interest is less than expected prior to the option listing. We can infer that such a firm is more short-sale constrained relative to other firms in the sample. Conversely, when τ is large, the stock is ex-ante unconstrained in a relative sense.

A potential problem with using τ as a measure of the degree of constraint relaxation is that we must assume that the proxies chosen for BETA and σ_E sufficiently purge EARSI of demand factors so that the supply (i.e., short-sale) constraint predominantly determines the magnitude of τ. Given the prior empirical evidence in Table 5-9, one can find some comfort in using Equation 8 as a purging regression. Recall that the adjusted R-squares presented in Table 5-9 are greater than .08 in some of the cases presented. This high R-square suggests that Beta and σ_E are reasonably good predictors of EARSI.

Empirical Tests—Interacting with the PUT Dummy

We now turn to the specification used to discern whether the degree of short-sale constraint relaxation effects either the change in share price or short interest level. Model 13 uses the variable PUT, which takes on the value of one if puts are introduced jointly with calls and zero otherwise.

Model 13: Interacting with the PUT Variable – Effects on Abnormal Returns

$$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 PUTBETA + \alpha_4 PDISPER + \alpha_5 PUT + \alpha_6 ABVOL + \alpha_7 ALPHA \quad (1)$$

AR = abnormal returns as calculated using 6 methods discussed above

BWCAR11 Brown and Warner CARs over an 11 day window
BWCAR6 Brown and Warner CARs over a 6-day window
NOALPH11 Brown and Warner CARs with α=0 (11 days)
NOALPH6 Brown and Warner CARs with α=0 (6 days)
ABRET11 Stock return less Market Return over 11 days

ABRET6 Stock return less Market Return over 6 days

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1 a single market factor model

SUMBETA the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW Standard deviation of the market model error in days t-100 to t-6

SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6

SDR1 Standard deviation of raw returns in days t-100 to t-6

SDR5 Standard deviation of five day raw returns in days t-100 to t-6

IBES The standard deviation of IBES long-term growth estimates

PUT = a dummy equal to 1 if a put is introduced simultaneously with a call, zero otherwise

PUTBETA = PUT×BETA

PDISPER = PUT×σ_E

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)

Since we hypothesize that the introduction of put options results in greater constraint relaxation than the listing of call options alone, the coefficient on PUT should be negative. Moreover, without the support of strong theoretical predictions, we nevertheless expect the effects of BETA and σ_E to be more pronounced when the constraint is relaxed more fully. Therefore, PUTBETA and PDISPER should carry negative signs. Other variables should carry the signs we have previously observed.

Table 6-1 provides results for this regression using ABRET11 as the abnormal return measure. Selection of this measure is somewhat arbitrary, and the results presented in Table 6-1 have been replicated for the other 5 abnormal return measures without important deviation from the Table 6-1 results. Care must be taken in reading Table 6-1 since the variables PUTBETA and PDISPER vary across regression specifications. For example, in the first specification BETA1 proxies for BETA and SDR1 proxies for σ_E so that PUTBETA equals the product of the variables PUT and BETA1 while PDISPER is the product of variables PUT and SDR1. In each column, a different combination of

BETA and σ_E proxies are used so that the PUTBETA and PDISPER combinations will also vary across observations.

Unfortunately, Table 6-1 presents no evidence that PUT, PUTBETA and PDISPER possess any explanatory value. The signs on PUTBETA and PDISPER are not even consistently negative for various combinations of BETA and σ_E. Perhaps more importantly, the hypothesis that PUT, PUTBETA and PDISPER are jointly zero cannot be rejected. An F-test of this hypothesis yields upper tail p-values (not shown) above the five percent significance level in only one of the eight specifications presented in the table. The other seven p-values average only .79. These low p-values on the F-test do not allow us to reject the hypothesis that PUT and its interactions fail to improve on the empirical models presented in Chapter 5. In short, PUT appears to add nothing to our model.

Notice that the BETA and σ_E proxies no longer produce overall results strongly consistent with those previously observed in Chapter 5. However, the BETA and σ_E coefficients now merely represent cross-sectional differences among call-only listings. For the set of joint listings, we must sum the coefficients on BETA and PUTBETA to obtain the proper coefficient for the set of joint listings just as we must sum the coefficients on σ_E and PDISPER to obtain the effects of dispersion on ABRET11 for the joint-listings subset. Although not shown, the results for the joint listings are consistent with Chapter 5 in that these summed coefficient values are negative and modestly significant or near significant in a statistical sense. Moreover, when PUT is included in the regression without PUTBETA and PDISPER, BETA and σ_E return to their previously observed magnitude and significance. However, PUT remains insignificant.

In summary, the interaction terms show no evidence of relevance in any of the specifications and PUT also is not impactful. However, BETA and σ_E remain modestly relevant for the subsample of joint listings and for the entire sample when the interaction terms are excluded from the regression.

Next, we turn to the effects of PUT and the interaction terms on ΔRSI. This analysis is conducted via Model 14 that follows:

Model 14: Interacting with the PUT Variable – Effects on ΔRSI

$$\Delta RSI = \alpha_0+\alpha_1 BETA+\alpha_2\sigma_E+\alpha_3 PUTBETA+\alpha_4 PDISPER+\alpha_5 PUT+\alpha_6 ABVOL+ \alpha_7 ALPHA+\alpha_7 ONE\ MONTH \quad (2)$$

ΔRSI = the change in monthly reported short interest scaled by shares outstanding
BETA = the Beta in the 95 trading days preceding the event window computed as either
BETA1 a single market factor model
SUMBETA the sum of beta coefficients on the contemporaneous and lagged market return
σ_E =a proxy for dispersion of expectations. The five alternative proxies are:
SDEBW Standard deviation of the market model error in days t-100 to t-6
SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6
SDR1 Standard deviation of raw returns in days t-100 to t-6
SDR5 Standard deviation of five day raw returns in days t-100 to t-6
IBES The standard deviation of IBES long-term growth estimates
PUT = a dummy equal to 1 if a put is introduced simultaneously with a call, zero otherwise
PUTBETA = PUT×BETA
PDISPER = PUT×σ_E
ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)
ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

Again, we hypothesize that the introduction of put options produces greater constraint relaxation. Therefore, for the left-hand-side variable ΔRSI, the coefficient on PUT should be positive since ΔRSI rises upon option listing. We also hypothesize that PUTBETA and PDISPER will carry positive signs if increased marginal constraint

relaxation causes the effects of BETA and σ_E to more strongly impact ΔRSI. Other variables will be unchanged from the results previously observed.

Table 6-2 provides results. As in previous regressions with ΔRSI as the left-hand-side variable, the regression is weighted to account for the simultaneous use of one and two month changes in short interest. White's correction is also employed. Once again, PUT, PUTBETA and PDISPER do not support the hypotheses offered. An F-test of the hypothesis that PUT, PUTBETA and PDISPER are jointly zero (not shown) cannot be rejected with mean p-values of .37 across all eight specifications. Moreover, PUT carries the "wrong" sign, and PUTBETA and PDISPER, though they are correctly signed in 15 of 16 cases, are never statistically significant.

Not shown in the table are the sum of the σ_E and PDISPER coefficients and the sum of the BETA and PUTBETA coefficients. The values for the sum of the coefficients for σ_E and PDISPER are consistently positive and significant for all dispersion proxies except IBES. The values of BETA and PUTBETA coefficients are consistently positive but generally statistically insignificant. However, they near significance in each instance and are highly significant when IBES serves as the dispersion measure. These results imply that the subset of joint listings produces results that are qualitatively similar to the overall sample results.

It is also worth noting that when Model 14 is rerun without the interaction terms, the PUT coefficient is positive and significant at the 1% level in all eight specifications. This is consistent with the joint hypothesis that PUT corresponds to a more complete elimination of the constraint and that less constrained stocks evidence an increase in

relative short interest. However, we must not over-interpret this result as it has been observed that PUT also may proxy for early versus recent year option listing.

In summary, the interaction terms do not support the hypotheses presented, but PUT does possess the correct sign with statistical significance when the interaction terms are omitted from the model.

Robustness Checks

As previously discussed, one problem with using PUT as a proxy for the degree of constraint relaxation is that joint listings dominate the later years of the sample while call-only listings comprise the first part of the sample. Therefore, PUT also proxies for late-in-the-sample listings. Robustness checks have been conducted by creating a new variable "LATE ," which explicitly controls for the timing of option listings. The variable LATE equals one for listings after 1986 and equals zero for listings between 1981 and December 31, 1986. Adding LATE to Model 13 yields the following revised model.

Model 13 revised:

$$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 PUTBETA + \alpha_4 PDISPER + \alpha_5 PUT + \alpha_6 ABVOL + \alpha_7 ALPHA + \alpha_8 (LATE*BETA) + \alpha_9 (LATE*\sigma_E) + \alpha_{10} LATE$$

LATE = a dummy equal to 1 for listings after December 31, 1986, zero otherwise

Obviously, this revised model is constructed to separate the effects of joint listings from temporal effects. Before discussing the impact of LATE on the other coefficients in the above model, I first turn to the question of whether LATE improves the specification relative to the original Model 13. Specifically, I jointly test whether $\alpha_8=0$, $\alpha_9=0$, and $\alpha_{10}=0$ using the same eight combinations of BETA and σ_E presented in Table 6-1. Unreported F-tests of the hypothesis reject this hypothesis at the 5% level in three

instances and at the 10% level in two of the other specifications. Thus, some support exists for including LATE as an explanatory variable.[3]

Given some comfort that LATE adds value to the regression, I turn my attention to the question of whether PUTBETA and PDISPER evidence the hypothesized negative coefficients. Surprisingly, both coefficients are negatively signed for all eight regression specifications. Moreover, for the BETA proxy SUMBETA, the results are highly significant in each regression[4]. Only one of the PDISPER variants is negative at the 5% level. These results would suggest that the PUT variable produces results consistent with the hypothesis that joint listings more greatly relax a security's short-sale constraint.

Unfortunately, these results are rather fragile. For example, using December 31, 1987 as the bifurcation date for the LATE dummy causes PUTBETA to cease to evidence a statistically significant negative sign, and PUTBETA is actually positive at a 5% level in one specification. However, the December 31, 1987 bifurcation results in increased significance for PDISPER, which is negative and significant for all specifications not involving IBES. When December 31, 1988 is used as the cutoff, neither PUTBETA nor PDISPER can be said to be nonzero in any of the eight specifications.

As a separate effort to control for intertemporal effects, I trifurcate the sample and generate two time dummies. The dummy EARLY equals one for the earliest third of the

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[3] Using a cutoff date of December 31, 1987 yields slightly lower F-statistics with p-values generally significant at the 10% level. A cutoff date of December 31, 1988 yields p-values that fail to reject at almost any conceivable level of significance.

[4] T-statistics for (PUT*SUMBETA)are –2.14 when included in a regression with SDR1 and attain even greater significance when SDR5, SDESUMB, and IBES are used as the dispersion proxies.

listings (zero otherwise), and LATE equals one for the latest third of the sample listings (zero otherwise).[5] This effort meets with mixed results. On one hand, an F-test of the hypothesis that coefficients on EARLY, LATE, and the four EARLY and LATE interactions terms are jointly zero are generally rejected at a 5% level. Also, we generally reject the hypothesis that the coefficient on (LATE*BETA) equals the coefficient on (EARLY*BETA), and we reject equality of coefficients for (LATE*σ_E) and (EARLY*σ_E) as well. Taken together, we can conclude that inclusion of these time dummies improves the fit of the model and that early listings differ from late listings in some manner independent of the joint listing versus call-only listing effects captured by the PUT variable.

However, relative to the time bifurcation method applied above, the trifurcation method produces no evidence that PUTBETA is negative (as hypothesized). PDISPER, while significantly negative in three of the six non-IBES specifications, is actually positive along with BETA in one of the regression.

In summary, controlling for intertemporal effects generally results in improved overall model fit as evidenced by occasionally significant p-values on various F-tests conducted in these robustness tests. Moreover, the PUTBETA and PDISPER variables are occasionally significantly negative for the models that control for intertemporal changes. However, the results are not unambiguously supportive of the joint hypotheses

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[5] Alternatively, EARLY equals one for pre-1986, and LATE equals one for post-1990. The results are similar for both trifurcation methods.

that PUT proxies for constraint relaxation and greater constraint relaxation produces greater negative share price adjustments upon option listing.

In addition to revising Model 13, Model 14 was also altered to include the same set of LATE and EARLY variables (including interaction terms). These variables provide no additional explanatory power to the model and PUTBETA and PDISPER are never negative at statistically significant levels for these tests. In short neither the original Model 14, for which results are presented in Table 6-2, nor any "intertemporally enhanced" variant tested can be said to support the hypotheses offered in this chapter.

Empirical Tests—Interacting with the TAU Variable

Having observed relatively unsatisfying results from the use of PUT as a proxy for constraint relaxation, I next turn to the residuals in the EARSI purging regression as a possible proxy. This non-simultaneous two equation model takes the following form:

Model 15: Interaction with Tau—Effects on abnormal returns

$AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 TAUBETA + \alpha_4 TDISPER + \alpha_5(\tau) + \alpha_6 ABVOL + \alpha_7 ALPHA$ (3)

$EARSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \tau$ (4)

AR = abnormal returns as calculated using 6 methods discussed above

- BWCAR11 Brown and Warner CARs over an 11 day window
- BWCAR6 Brown and Warner CARs over a 6-day window
- NOALPH11 Brown and Warner CARs with $\alpha=0$ (11 days)
- NOALPH6 Brown and Warner CARs with $\alpha=0$ (6 days)
- ABRET11 Stock return less Market Return over 11 days
- ABRET6 Stock return less Market Return over 6 days

BETA = the Beta in the 95 trading days preceding the event window computed as either

- BETA1 a single market factor model
- SUMBETA the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

- SDEBW Standard deviation of the market model error in days t-100 to t-6
- SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6
- SDR1 Standard deviation of raw returns in days t-100 to t-6

SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates
TAUBETA=	BETA × τ
TDISPER=	$\sigma_E \times \tau$
τ=	the residual in Equation 4
ABVOL =	Additional daily volume in the event window (scaled by outstanding shares)
ALPHA =	the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)
EARSI=	Short Interest prior to the option introduction divided by outstanding shares.

The above system of equations consists of two OLS regressions where Equation 22 is run first so that the error term from Equation 22 can be inserted into Equation 21.[6] Since τ is large when the stock is relatively unconstrained prior to the option listing, we hypothesize that the coefficient on τ in Equation 21 will be positive (i.e. the stock price will not fall as much for large τ stocks). Likewise, the effects of BETA and σ_E should be felt less when τ is large, so the coefficients on TAUBETA and TDISPER in Equation 21should be positive also. The signs on all other coefficients should conform with results seen previously.

The results of Model 15 are presented in Table 6-3 with only the results of Equation 21 shown. Once again, results are presented for ABRET11 with the caveat that the five other abnormal return metrics produce qualitatively similar results. As was the case for the PUT interactions, we find that the interaction terms in Model 15 provide very little support for the hypotheses tested. To begin with, TAUBETA and TDISPER carry the wrong signs. Although these terms are signed incorrectly, TDISPER is never

[6] Although τ is a generated regressor, because τ is the error term from the first regression it does not produce the biased t-statistics commonly associated with generated regressors. Pagan(1984) shows that a generated error does not produce a generated regressor bias.

statistically significant, and TAUBETA is significant at the 5% level for only one of the regressions. An F-test of the hypothesis that TAU=TAUBETA=TDISPER=0 is rejected at the 5% level in only one of the eight specifications. The remaining specifications could not be rejected at even the 10% level.

Turning to the coefficient on the uninteracted τ variable, we find it is not significantly different from zero in any specification, and the wrong sign is present in four of eight specifications. However, when the interactive terms, TAUBETA and TDISPER, are removed from Model 15, the coefficient on τ in Equation 21 is negative (the "wrong" sign) and statistically significant in six of eight specifications (five specifications at the 1% level). The two "IBES specifications" have insignificant coefficients on τ. The other five abnormal returns metrics (not shown) produce similar results for the τ coefficients, but at borderline statistical significance levels.

Let us turn to the effects of τ interactions on ΔRSI. These effects are examined through analysis of Model 16, which follows the same design as Model 15.

Model 16: Interaction with Tau—Effects on ΔRSI

$$\Delta RSI=\alpha_0+\alpha_1 BETA+\alpha_2\sigma_E+\alpha_3 TAUBETA+\alpha_4 TDISPER+\alpha_5(\tau)+\alpha_6 ABVOL +\alpha_7 ALPHA+\alpha_8 ONEMONTH \quad (5)$$

$$EARSI=\alpha_0+\alpha_1 BETA+\alpha_2\sigma_E+\tau \quad (6)$$

ΔRSI= the change in monthly short interest scaled by shares outstanding.

BETA = the Beta in the 95 trading days preceding the event window computed as either

- BETA1 a single market factor model
- SUMBETA the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

- SDEBW Standard deviation of the market model error in days t-100 to t-6
- SDESUMB Standard deviation of the summed beta model error in days t-100 to t-6
- SDR1 Standard deviation of raw returns in days t-100 to t-6
- SDR5 Standard deviation of five day raw returns in days t-100 to t-6

IBES The standard deviation of IBES long-term growth estimates
TAUBETA= BETA × τ
TDISPER= $\sigma_E \times \tau$
τ= the residual in Equation 6
ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)
EARSI = Short Interest prior to the option introduction divided by outstanding shares.
ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

Since τ is large when the stock is relatively unconstrained prior to the option listing, we hypothesize that the coefficient on τ in Equation 23 will be negative (i.e. ΔRSI will not increase as much for stocks that already evidenced unusually large short interest levels prior to the option listing. Likewise, the effects of BETA and σ_E should be felt less when τ is large, so the coefficients on TAUBETA and TDISPER in Equation 23 should be negative also. The signs on all other coefficients should conform with results seen previously.

Does the new specification provide support for the hypotheses? Not much. First, an F-test of the hypothesis that TAU=TAUBETA=TDISPER=0 is rejected in none of the specifications. Also, notice that TAUBETA and TDISPER frequently carry a positive sign rather than the anticipated negative one. Clearly this does nothing to support the contention that differential constraint relaxation is evidenced in the interaction terms. Turning to the coefficient on τ, although the reported values are not statistically significant, at least several of these numbers bear the anticipated arithmetic sign at near-significant levels. However, before interpreting this most modest of outcomes as evidence that τ is functioning in its assigned role as a constraint level proxy, let me acknowledge

that a positive value of τ might be expected even on a random sample of firms if short interest is mean reverting. In other words, one might interpret a negative value on τ as confirmation that firms with high short interest levels in one month tend to go down in the next month while firms with low short interest mean revert to higher levels. Given this caveat and the weak nature of the results anyway, I must conclude that the data do not provide any comfort that the hypotheses are empirically supported by this model.

When the interactive terms, TAUBETA and TDISPER, are removed from Model 15, the coefficient on τ in Equation 23 remains insignificantly negative.

Robustness Checks

In addition to the tests described above, several robustness checks have been conducted without significant deviation from the above findings. For example, I have conducted several probit tests using zero-one dummies for ΔRSI. These have been executed using a bifurcation method (if ΔRSI>0, dummy=1--otherwise, dummy=0) or throwing out the middle third of the observations (if ΔRSI in highest third, dummy=1--if ΔRSI in lowest third, dummy=0). The results are essentially unchanged as a result of these modifications.

These same probit techniques also have been applied to variants of Model 15. Again, the results are not substantively altered. In addition to these robustness checks, I should also note that other proxies have been considered as measures of constraint relaxation. For example, option market makers suggest that Nasdaq stocks are more difficult to short than NYSE stocks. One might interpret this observation as suggesting that less constraint relaxation occurs upon the option listing of a Nasdaq stock than an

exchange traded stock because option market have greater difficulty intermediating the desired short sales. On the other hand, the short selling problems encountered by the option market makers may, nevertheless, be less severe than those faced by other investors. In that case, the degree of listing-related constraint relaxation may be greater in a Nasdaq stock although the remaining short-sale constraint may still be larger than for exchange traded stocks. In short, while we might expect that the trading locale of the underlying stock is important, the impact of this factor on the degree of constraint relaxation is ambiguous.

Despite this ambiguity, I have tested the stock's trading locale as a possible proxy for the degree of constraint relaxation. The variable NASD was included as a right-hand-side variable along with NASD×BETA and NASD×σ_ε in models similar to those presented previously in this chapter. No table is used to present these results, but a brief summary analysis follows.

To begin, the three variables show no evidence of empirical importance when all three are included in regressions using either ΔRSI or abnormal return proxies as regressands. However, Nasdaq firms clearly have greater increases in short interest levels than exchange traded firms as evidenced by significant coefficients observed when only NASD is added to the usual regressor list. Despite the statistical significance observed in this ΔRSI regression, abnormal returns are unaffected by the NASD dummy in similar tests.

Given the potential conflict between competing hypotheses for the NASD dummy and the absence of important results in the tests themselves (except one regression using

ΔRSI as the regressand), I am unwilling to attach any credibility to NASD as a proxy for constraint relaxation.

Summary and Conclusions

The abnormal return measures showed little evidence that the chosen proxy variables have the expected importance either directly or via interaction terms. In fact, the τ variable possesses the wrong coefficient sign when included without interaction terms as a regressor in Model 15. Using ΔRSI as the regressand produces more promising results when interaction terms are excluded from either Model 14 or Model 16. In those cases, both PUT and τ have the expected coefficients at significant levels. However, these results may have more pedestrian explanations than the hypotheses offered. PUT may function as an "early year versus late year" proxy, and τ may merely evidence a tendency toward mean reversion.

To control for intertemporal difference when PUT is used as a proxy for the degree of constraint relaxation, I consider various time-related dummies to separate early-year from later-year listing events. These alternatives show modest support for the hypotheses tested in this section in that the fit of the model is improved occasionally and the coefficients on various PUT interaction terms (PUTBETA and PDISPER) usually evidence the anticipated sign and occasionally evidence statistical significance. However, taken as a whole, this chapter presents weak evidence that stocks with joint listings produce greater constraint relaxation than call-only listings.

Table 6-1
Model 13: Interacting with the PUT Variable –Effects on Abnormal Returns

	Model 13							
Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
# of Observations	1426	1426	1426	1426	1426	1426	857	857
Mean of Dep. Var.	0.1275	0.1275	0.1275	0.1275	0.1275	0.1275	-0.0625	-0.0625
Standard Error	7.2953	7.2991	7.2957	7.2965	7.1626	7.2974	6.6447	6.6467
R-Squared	0.0140	0.0129	0.0139	0.0136	0.0495	0.0134	0.0187	0.0181
Adjusted R-Squared	0.0091	0.0081	0.0090	0.0088	0.0448	0.0085	0.0106	0.0100
F-statistic	2.87	2.65	2.85	2.80	10.56	2.75	2.31	2.24
Log of Likelihood Func.	-5126.30	-5127.04	-5126.37	-5126.53	-5100.11	-5126.70	-2974.34	-2974.60
CONSTANT	1.6699	0.9956	2.1879	1.5021	2.2755	0.9299	0.6638	-0.4707
	1.52	0.89	1.93*	1.30	2.20*	0.82	0.57	-0.40
BETA1	-1.4452		-1.1119		-1.3399		-1.1281	
	-1.77*		-1.45		-1.77*		-1.19	
SUMBETA		-0.1510		0.0701		-0.2297		-0.0289
		-0.19		0.09		-0.30		-0.03
SDR1	5.5112	-33.0494						
	0.11	-0.64						
SDR5			-20.6685	-38.0043				
			-0.83	-1.52				
SDEBW					-107.0333			
					-0.63			
SDESUMB						-29.3209		
						-0.51		
IBES							0.0016	0.0013
							1.12	0.90

Table 6-1--continued

Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
PUTBETA	0.8208	-0.4893	0.3539	-0.8031	0.8914	-0.3822	0.7966	-0.3868
	0.89	-0.55	0.41	-0.96	1.00	-0.45	0.76	-0.37
PDISPER	-36.7995	4.0071	13.0934	31.2211	-246.2210	-10.2712	-0.0012	-0.0009
	-0.61	0.06	0.45	1.05	-0.97	-0.15	-0.80	-0.58
PUT	-0.4494	0.2857	-1.1874	-0.4504	0.7722	0.4663	-0.5632	0.7117
	-0.33	0.21	-0.86	-0.33	0.50	0.34	-0.42	0.54
ABVOL	0.0866	0.0863	0.0880	0.0862	0.2451	0.0900	-0.2597	-0.2595
	0.40	0.40	0.41	0.40	1.58	0.42	-0.64	-0.65
ALPHA	2.5065	2.7336	2.5100	2.7216	2.2427	2.8134	2.1703	2.3064
	2.51**	2.76**	2.50**	2.73**	2.31*	2.84**	1.84*	1.95

I estimate the following regression model:

(1) $AR = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 PUTBETA + \alpha_4 PDISPER + \alpha_5 PUT + \alpha_6 ABVOL + \alpha_7 ALPHA$

for the sample of post-1980 option introductions. The dependent variable is defined as
AR = abnormal returns as calculated using ABRET11 defined as the stock return less Market Return over 11 days

Independent Variables are:
BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6

Table 6-1--continued

IBES The standard deviation of IBES long-term growth estimates
PUT = a dummy equal to 1 if the a put is introduced simultaneously with a call, zero otherwise
PUTBETA = PUT × BETA
PDISPER = PUT × σ_E
ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)

Note: Five other abnormal return measures have been tested in place of ABRET11 without material contrast to the above results.

Table 6-2
Model 14: Interacting with the PUT Variable –ΔRSI

	Model 14							
Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
# of Observations	1309	1309	1308	1308	1309	1309	787	787
Mean of Dep. Var.	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0020	0.0020
Standard Error	0.0162	0.0161	0.0162	0.0162	0.0162	0.0161	0.0112	0.0113
R-Squared	0.0936	0.0965	0.0901	0.0934	0.0864	0.0957	0.0388	0.0351
Adjusted R-Squared	0.0880	0.0909	0.0845	0.0878	0.0808	0.0902	0.0290	0.0252
F-statistic	16.79	17.35	16.07	16.72	15.37	17.21	3.93	3.54
Log of L'hood Func.	3476.36	3480.52	3469.95	3474.53	3471.50	3479.27	2416.92	2415.63
CONSTANT	-0.0026	-0.0024	-0.0026	-0.0023	-0.0012	-0.0025	0.0002	0.0007
	-1.57	-1.51	-1.37	-1.28	-0.58	-1.69 *	0.21	0.69
BETA1	0.0010		0.0010		0.0017		0.0007	
	0.71		0.85		1.56		0.81	
SUMBETA		0.0005		0.0005		0.0006		0.0003
		0.50		0.58		0.64		0.30
SDR1	0.0745	0.0873						
	1.23	1.64						
SDR5			0.0356	0.0417				
			1.38	1.78 *				
SDEBW					-0.0854			
					-0.78			
SDESUMB						0.0980		
						1.46		
IBES							1.64E-07	2.68E-07
							0.28	0.42
PUTBETA	-0.0002	0.0008	0.0002	0.0010	0.0002	0.0009	0.0012	0.0011
	-0.09	0.56	0.12	0.80	0.10	0.62	1.00	0.92
PDISPER	0.1262	0.0891	0.0267	0.0137	0.2878	0.0654	0.00001	0.00001
	1.15	1.00	0.76	0.43	1.51	0.67	0.70	0.70

Table 6-2--continued

Dependent Variable	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI	ΔRSI
PUT	-0.0011	-0.0016	0.0003	-0.0003	-0.0001	-0.0010	-0.0006	-0.0008
	-0.53	-0.79	0.12	-0.16	-0.03	-0.53	-0.45	-0.55
ABVOL	0.0008	0.0008	0.0008	0.0008	0.0007	0.0008	0.0004	0.0004
	2.71 **	2.80 **	2.71 **	2.80 **	2.63 **	2.78 **	2.28 *	2.38 **
ALPHA	0.0023	0.0023	0.0025	0.0025	0.0045	0.0024	0.0006	0.0006
	1.14	1.07	1.16	1.08	1.77 *	1.10	0.33	0.32
ONEMONTH	-0.0014	-0.0014	-0.0014	-0.0014	-0.0015	-0.0014	-0.0006	-0.0006
	-1.83 *	-1.81 *	-1.86 *	-1.82 *	-1.89 *	-1.80 *	-0.74	-0.71

I estimate the following regression model:

(2) $\Delta RSI = \alpha_0 + \alpha_1 BETA + \alpha_2 \sigma_E + \alpha_3 PUTBETA + \alpha_4 PDISPER + \alpha_5 PUT + \alpha_6 ABVOL + \alpha_7 ALPHA + \alpha_7 ONEMONTH$

for the sample of post-1980 option introductions with short interest data available. The dependent variable is defined as

ΔRSI = the change in monthly reported short interest scaled by shares outstanding

Independent Variables are:

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

PUT = a dummy equal to 1 if the a put is introduced simultaneously with a call, zero otherwise

PUTBETA = PUT × BETA

PDISPER = PUT × σ_E

ABVOL = Additional daily volume in the event window (scaled by outstanding shares)

ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)

ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

All t-statistics are computed using Whites heteroskedasticity correction.

Table 6-3
Model 15: Interaction with Tau—Effects on abnormal returns

	Model 15							
Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
# of Observations	1333	1333	1333	1333	1333	1333	802	802
Mean of Dep. Var.	0.1976	0.1976	0.1976	0.1976	0.1976	0.1976	-0.0181	-0.0181
Standard Error	7.2278	7.2315	7.2267	7.2307	7.1119	7.2301	6.6434	6.6477
R-Squared	0.0138	0.0128	0.0141	0.0130	0.0451	0.0131	0.0229	0.0216
Adjusted R-Squared	0.0086	0.0076	0.0089	0.0078	0.0401	0.0079	0.0143	0.0130
F-statistic	2.65	2.45	2.70	2.49	8.95	2.52	2.66	2.51
Log of L'hood Func	-4782.40	-4783.08	-4782.20	-4782.94	-4760.87	-4782.84	-2785.36	-2785.88
CONSTANT	1.2630	1.2401	1.3108	1.2465	2.2690	1.3493	-0.2197	-0.2372
	2.02 *	2.04 *	2.10 *	2.10 *	3.72 **	2.24 *	-0.38	-0.43
BETA1	-0.7976		-0.7574		-0.7376		-0.2327	
	-1.94 *		-1.99 *		-1.92 *		-0.53	
SUMBETA		-0.5538		-0.5419		-0.5244		-0.1864
		-1.49		-1.53		-1.46		-0.48
SDR1	-18.2203	-25.1887						
	-0.66	-0.87						
SDR5			-11.1059	-13.0330				
			-0.93	-1.02				
SDEBW					-211.0067			
					-2.64 **			
SDESUMB						-35.4049		
						-1.17		
IBES							0.0010	0.0011
							1.61	1.61
TAUBETA	-10.5544	-2.1626	-11.4737	-3.5728	-12.0566	-2.6701	-24.0034	-16.9030
	-0.79	-0.21	-0.95	-0.37	-0.88	-0.26	-1.88 *	-1.56

Table 6-3--continued

Dependent Variable	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11	ABRET11
TDISPER	-78.0390	-424.4274	-81.1797	-202.3972	3565.3181	-428.1172	0.0192	0.0174
	-0.08	-0.49	-0.25	-0.64	0.61	-0.50	1.18	1.06
TAU (τ)	-3.1149	-3.7005	1.1736	-1.2879	-31.9160	-2.9643	8.4646	4.0793
	-0.13	-0.16	0.06	-0.06	-0.74	-0.13	0.48	0.27
ABVOL	0.0566	0.0531	0.0570	0.0550	0.1959	0.0546	-0.2446	-0.2445
	0.26	0.24	0.26	0.25	1.28	0.25	-0.59	-0.59
ALPHA	1.9216	1.9697	1.9901	2.0386	1.7632	2.0545	1.9426	1.9409
	1.98 *	2.03 *	2.02 *	2.08 *	1.86 *	2.11 *	1.61	1.60

I estimate the following regression model:

(3) $\mathbf{AR} = \alpha_0 + \alpha_1 \mathbf{BETA} + \alpha_2 \sigma_E + \alpha_3 \mathbf{TAUBETA} + \alpha_4 \mathbf{TDISPER} + \alpha_5(\tau) + \alpha_6 \mathbf{ABVOL} + \alpha_7 \mathbf{ALPHA}$

(4) $\mathbf{EARSI} = \alpha_0 + \alpha_1 \mathbf{BETA} + \alpha_2 \sigma_E + \tau$

for the sample of post-1980 option introductions where ex-ante short interest is available. The dependent variable is defined as
AR = abnormal returns as calculated using ABRET11 defined as the stock return less Market Return over 11 days

Independent Variables are:
BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

TAUBETA= BETA × τ

Table 6-3--continued

TDISPER= $\sigma_E \times \tau$
τ = the residual in Equation 4
ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)
EARSI=Short Interest prior to the option introduction divided by outstanding shares.

Only results for Equation 3 are presented, and all t-statistics are computed using White heteroskedasticity correction.
Note: Five other abnormal return measures have been tested in place of ABRET11 without material contrast to the above results.

Table 6-4
Model 16: Interaction with Tau—Effects on ΔRSI

	Model 16							
Dependent Variable	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI
# of Observations	1309	1309	1308	1308	1309	1309	787	787
Mean of Dep. Var.	0.0028	0.0028	0.0028	0.0028	0.0028	0.0028	0.0020	0.0020
Standard Error	0.0161	0.0160	0.0161	0.0161	0.0161	0.0160	0.0112	0.0113
R-Squared	0.1033	0.1062	0.0996	0.1028	0.0951	0.1062	0.0414	0.0379
Adjusted R-Squared	0.0978	0.1007	0.0940	0.0973	0.0896	0.1007	0.0316	0.0280
F-statistic	18.71	19.32	17.96	18.61	17.08	19.31	4.20	3.83
Log of L'hood Func	3487.79	3491.98	3483.63	3488.21	3481.83	3491.48	2417.28	2416.04
CONSTANT	-0.0040	-0.0043	-0.0029	-0.0032	-0.0018	-0.0040	-0.0002	0.0001
	-3.08 **	-3.22 **	-2.23 *	-2.50 **	-1.32	-3.05 **	-0.25	0.06
BETA1	0.0008		0.0012		0.0018		0.0018	
	0.58		0.95		1.63		2.60 **	
SUMBETA		0.0013		0.0015		0.0014		0.0014
		1.46		1.80 *		1.71 *		2.22 *
SDR1	0.1936	0.1736						
	2.50 **	2.81 **						
SDR5			0.0666	0.0608				
			2.48 **	2.61 **				
SDEBW					0.2268			
					1.79 *			
SDESUMB						0.1682		
						2.72 **		
IBES							0.0000	0.0000
							0.31	0.37
TAUBETA	0.0264	0.0174	0.0251	0.0170	0.0084	0.0201	0.0139	0.0064
	0.63	0.54	0.66	0.54	0.24	0.65	0.32	0.19

Table 6-4--continued

Dependent Variable	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI	DRSI
TDISPER	1.0076	1.2866	0.1881	0.2720	6.2205	0.9006	0.00001	0.00001
	0.36	0.52	0.20	0.30	1.29	0.37	-0.39	-0.40
TAU (τ)	-0.1219	-0.1215	-0.1017	-0.0990	-0.1161	-0.1126	0.0135	0.0238
	-1.46	-1.44	-1.23	-1.21	-1.51	-1.37	0.20	0.36
ABVOL	0.0008	0.0008	0.0008	0.0008	0.0007	0.0008	0.0004	0.0004
	2.72 **	2.81 **	2.76 **	2.83 **	2.60 **	2.78 **	2.32 *	2.44 **
ALPHA	0.0025	0.0025	0.0023	0.0023	0.0049	0.0024	0.0006	0.0006
	1.15	1.09	1.05	0.99	1.97 *	1.06	0.33	0.34
ONEMONTH	-0.0014	-0.0014	-0.0014	-0.0014	-0.0015	-0.0013	-0.0007	-0.0007
	-1.74 *	-1.73 *	-1.72 *	-1.71 *	-1.87 *	-1.66 *	-0.88	-0.88

I estimate the following regression model

(5) $\Delta RSI=\alpha_0+\alpha_1 BETA+\alpha_2\sigma_E+\alpha_3 TAUBETA+\alpha_4 TDISPER+\alpha_5(\tau)+\alpha_6 ABVOL+\alpha_7 ALPHA+\alpha_8 ONEMONTH$

(6) $EARSI=\alpha_0+\alpha_1 BETA+\alpha_2\sigma_E+\tau$

for the sample of post-1980 option introductions with short interest data available. The dependent variable is defined as ΔRSI= the change in monthly short interest scaled by shares outstanding.

Independent Variables are

BETA = the Beta in the 95 trading days preceding the event window computed as either

BETA1	a single market factor model
SUMBETA	the sum of beta coefficients on the contemporaneous and lagged market return

σ_E =a proxy for dispersion of expectations. The five alternative proxies are:

SDEBW	Standard deviation of the market model error in days t-100 to t-6
SDESUMB	Standard deviation of the summed beta model error in days t-100 to t-6
SDR1	Standard deviation of raw returns in days t-100 to t-6
SDR5	Standard deviation of five day raw returns in days t-100 to t-6
IBES	The standard deviation of IBES long-term growth estimates

Table 6-4--continued

TAUBETA= BETA × τ
TDISPER= σ_E τ
τ = the residual in Equation 6
ABVOL = Additional daily volume in the event window (scaled by outstanding shares)
ALPHA = the estimation period alpha value from the Brown/Warner market model (days t-100 to t-6)
EARSI =Short Interest prior to the option introduction divided by outstanding shares.
ONEMONTH= a dummy for a one-month ΔRSI measurement window (one month = 1, two months = 0)

Only results for Equation 5 are presented, and all t-statistics are computed using White heteroskedasticity correction.
using White heteroskedasticity correction.

CHAPTER 7
SUMMARY AND CONCLUSIONS

This paper presents both theoretical and empirical evidence that observed increases in short selling are related to the recently recognized negative abnormal returns reported by Sorescu (1997). I have developed a model that identifies stock trading and market characteristics that can be used to predict the magnitude of individual stock price declines. This model predicts that stocks evidencing high betas and high dispersion of investor opinion will respond to option listings with greater increases in short interest and more negative price responses.

Tests performed in Chapter 5 empirically confirm these predictions. Moreover, stocks evidence short interest levels prior to option introductions, which support the contention that investors are more likely to short stocks with high betas and high dispersion of investor valuations. The results in this chapter strongly support the thesis advanced in this paper.

Chapter 6 explicitly recognizes that cross-sectional differences in the degree of short-sale constraint relaxation probably exist because some firms are more short-sale constrained than others prior to option listing. Two alternative proxies for the degree of constraint relaxation are offered. Firms with a greater degree of short-sale constraint relaxation are expected to exhibit greater increases in short interest and more negative share price responses coincident with option listings. However, the empirical tests provide

only weak support for this contention. Obviously, such weak results may stem from a faulty theoretical foundation, poor proxy variables, or excessively noisy data.

Taken as a whole, this paper provides very strong evidence that option listing window returns and short interest level changes are linked. No previous work has documented a contemporaneous change in price and short interest level. Moreover, I find the degree of price and short-sale response around an option introduction is ex-ante predicted by the firm's beta and by the dispersion of investor expectations. This finding suggests that short-sale constraints may cause firms with high beta and high dispersion of investor expectations to be mispriced in the market. Recent high valuations for Internet stocks may result, in part, from this phenomenon. Likewise, long-run returns for initial public offerings may be a function of short-sale constraint levels, the dispersion of investor expectations and firm betas. A test of this hypothesis would be a logical extension of the findings reported in this thesis.

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